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Research Article

Optimum influence of kaolin additive and combustion characteristics of *Albizia zygia* wood-coconut-husk blends on ash yield

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Abstract: Property of solid fuel is characterized based on the amount of ash yield after combustion. This study evaluates the influence of kaolin additives and combustion characteristics of *Albizia zygia* wood and coconut husk mixture on ash yield. D-Optimal Design under the Combined Methodology of Design Expert was employed to mix the solid fuel constituents alongside particle size in order to determine the ash yield of the mixture. The input parameters (wood, coconut husk, kaolin, and particle size) and output parameter (ash yield) of combustion process were also modeled using Artificial Neural Network (ANN). The 23 data points obtained from design of experiment were divided into training data and testing data sets in the relative proportion 9:1. A quadratic regression model ($p<0.05$) was obtained for the ash prediction. The optimal values established for the ash yield were wood (85 %), coconut husk (5.0 %), kaolin (10 %) and particle sizes (2.50 mm) respectively. The coefficient of determination (R^2) obtained for the model is 0.8825 while the adjusted R^2 is 0.8153. The ANN (R^2) values for the model predictions were 0.939 for the training set and 0.926 for the testing set respectively. Thus, this study demonstrated that combustion of wood-coconut additive mixture could be efficient for energy generation.

Keywords: *Albizia zygia*; artificial neural network; ash yield; coconut husk; kaolin

1. Introduction

Long term utilization of fossil fuel for steam and power generation has doubled the global carbon dioxide (CO_2) emission over the past 50 years (Wang et al., 2012) Emission of these gasses has resulted into global warming and change of climatic conditions. To lessen the effect of environmental pollution, renewable energy is considered as the most viable option (Tugce et al., 2012) Biomass fuel is of different nature; depending on local availability and ranging from straw and forest residues to wood chips and standardized wood pellets. They are also considered environmentally friendly as combustion of biomass does not contribute to net rise in CO_2 (Oladosu et al., 2016). However, combustion of biofuel for power generation results in the release flue gases such as potassium (K), sodium (Na), calcium (Ca) and chlorine (Cl). These alkali metals are either present in raw biomass or released into the vapour phase, or retained in the solid phase as ash after combustion (Niu et al.,2013; Xiwen et al., 2020). At high temperatures during combustion, most of the inorganic and organic forms of potassium are volatile which results in the slagging and corrosion effects as they condense on the surfaces of heat transfer equipment (Hakan, 2012).

Blas (2014) reported high temperature Cl corrosion and fouling of superheater and reheater coils which are the most important in-furnace problems encountered during power generation from agro-biomass (Yongtie, et al., 2018;

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Diarmaid et al.,2018) and this often led to unscheduled power failure. KCl and K_2SO_4 content in biomass are the principal causative agents for ash-related problems and higher boiler corrosion as well as impediment of fly ash utilization due to high Cl content in the fly ash (Niu et al., 2016). To lessen the prevalent occurrences of these ash related issues during biomass conversion process, the use of additives (aluminium, calcium, phosphorus or sulphur based), co-firing, and leaching are generally employed during the combustion of biomass with high quantity of alkali metals (K, Cl and Na) (Yanqing et al. 2015). Additives are chemicals purposely used to mitigate ash deposition problems in the heat exchanger tubes and thereby changing the ash chemistry, reducing the formation of problematic compounds, and increasing the melting temperatures of ash residues (Bostrom et al., 2009). Wang et al. (2012) reported various additive mechanisms; chemical adsorption, physical adsorption, increasing ash melting temperatures or preventing ash sintering during biomass combustion. Past studies have proved the use of additives efficacy for elimination of ash sintering and slagging in combustion of biomass pellets (Wang et al., 2018; Qian et al., 2017; Kareem et al., 2018 & Xiong et al., 2008). Kaolin contains kaolinite ($Al_2Si_2O_5(OH)_4$), appears to be a good option for solving ash-related problems because of its sorptive characteristic for potassium sequestration (Katsuya, and Ichiro 2011)

Wood (*Albizia zygia*) has a characteristic low ash content and high gross calorific value (Ogunsola et al., 2018) and in form of sawdust; a waste wood gotten from a sawmill, discourage deforestation and utilization of waste for energy generation, the use of wood biomass becomes imperative because it is readily available and of lower cost compared to fossil fuels. Wood biomass is sufficiently and effectively combusted in a furnace with a significant reduction in total emission of greenhouse gases, principally (CO_2), methane (CH_4) and nitrous oxide (Blas, 2014). However, (Christian et al., 2019) reported that the potassium (K) content of the wood fuel influences the formation of particulate matters and these findings are in line with the work of (Sippula et al., 2007) that K is the dominating element followed by sulphur (S) and chlorine, thus the most relevant inorganic particulate matter fractions are K_2SO_4 and KCl. Marthians (2019) reported that kaolin as an additive in wood pellet combustion with several mixtures of spruce and short rotation- coppiece (SRC)- willow and its influence on emissions and ashes, the results showed that addition of kaolin reduced particulate matters even in lowest kaolin concentration (0.2 wt %) in every combination of spruce and SRC-willow. Potential additives for small-scale wood chip combustion using five different additives (kaolinite, anorthite, calcium silicate, titanium dioxide and aluminum hydroxide) in a pilot scale was investigated by (Marthians, 2019), His findings showed that additives kaolinite anorthite and aluminum hydroxide were the most promising ones based on reduction in particulate matters

Coconut husk forms the majority of the waste 35-40% of the coconut fruit. Dedie et al. (2014) reported that coconut husk could be used as a biomass fuel for steam generation due to its high calorific value. Large quantities of this waste are still left unused or burnt in developing countries. Teixeira et al. (2012) reported that the slagging propensity during the co-firing of coconut husk and coal blends in a fluidized bed combustor was bearable, and concluded that the biomass could be utilized as bio-fuel without severe fouling and slagging problems. This paper conducts statistical analysis of kaolin additive and combustion characteristics vis a vis D optimal and artificial neural network analytical tool.

2. Methods

2.1. Sample collection and preparation

The sawdusts of *Albizia* zygia wood were obtained from sawmill situated Pakiotan Area, Ogbomoso while the coconut husks were obtained from a farm in Ogbomoso, Nigeria. The materials were transported to Department of Pure and Applied Chemistry Laboratory LAUTECH Ogbomoso, Nigeria and kept in an electric dryer (line series) for 48 hrs to eliminate considerable moisture content. The kaolin with particle size 100 μm was commercial grade and supplied in powder form.

2.2. Theory of optimal mixture design

The DOE technique provides an efficient means of optimizing experimental processes as well as determining the optimal formulation of a specific mixture. The input variables or components of Mixture Methodology are non-negative proportionate amounts of the mixture and the relationship is expressed as percentage of the mixture, with the sum equal to 100. Furthermore, in mixture DOE, the measured response is assumed to depend only on the relative proportions of the mixture components and not on the whole volume of the mixture (Zahra et al., 2012). In most mixture designs, there are some bound restrictions on the component proportions X_j which limit the feasible space of variables between the lower L_j and upper H_j constraints. The general form of the constrained mixture problem is:

$$\sum_f X_f = 100 \; and \; L_f \leq X_f \leq H_f \qquad (1)$$

In mixture DOE, optimizing the response variable (Y) is desirable based on the experimental values of the independent factors, (X)

$$Y = f(X_1, X_2 X_3 \dots\dots X_n) \quad (2)$$

The independent variables are assumed to be continuous and controllable by experiments with negligible errors. Finding a suitable approximation for the true functional relationship between the independent variables and the response surface is required. The response was used to develop an empirical model that correlated the response, ash contents to the independent variables which are the fractions of wood (*Albizia zygia*), coconut husk, kaolin as well as particle size

A mixture DOE typically involves the following six steps:

i. Selection of a suitable technique of mixture DOE: There are several available mixture design techniques. An appropriate technique is selected based on the ranges of the independent variables or bound restrictions. Simplex designs can be used whenever the components form a simplex region; in other words, when the ranges of independent variables are equal. On the other hand, an optimal design is the right selection when the bound restrictions are non-simplex or the same size.
ii. Identification of the name, unit and the bound restrictions of mixture components.
iii. Identification of the name and unit of the responses.
iv. Proposition of an appropriate model to find the relationship between the responses and the mixture components.
v. Running all the determined experiments designed by the model one by one according to the run numbers.
vi. Entering the achieved responses from the experimental results

Scheffé's linear (Eq. (3)) or quadratic (Eq. (4)) polynomials were employed to fit the properties of the formulations to the weight contents of their components (Henrique et al., 2020). The polynomial fit quality was assessed based on the regression coefficient R^2 and adjusted R^2. The analysis of variance was also applied to determine the statistical significance of the models and the lack of fit of the model.

In these equations, X_i is the weight or volumetric fraction of the i-th component, q is the number of components in the experimental design, $\hat{y}$ is the value predicted by the model for the property under analysis, and β_i and β_{ij} are constant polynomial coefficients.

$$\hat{y} = \sum_{i=1}^{q} \beta_i X_i \quad (3)$$

$$\hat{y} = \sum_{i=1}^{q} \beta_i X_i + \sum \sum_{i<j}^{q} \beta_{ij} X_i X_j \quad (4)$$

2.3. Experimental design

D-optimal Design under the Combined Methodology of Design Expert (7.1.6 version) was employed to optimize the mixture components and process factor (particle size). The mixed ratio of the wood and coconut husk was between 5 and 95 %, while the kaolin (additive) was between 0 and 10 %. The particle size ranged from 1 to 4 mm (Table 1). The 23 experimental runs generated were used to investigate the effect of kaolin and combustion characteristics of the mixtures of wood, coconut husk and particle size on ash yield.

Table 1: Minimum and Maximum level of Components and Factor selected

Mixture	Code	Units	Level	
			Minimum	Maximum
	WD	%	5.0	95.0
Components	CH	%	5.0	95.0
	KL	%	0.0	10.0
Factor	PS	mm	1.0	4.0

WD= wood, CH = coconut husk, KL= kaolin, PS=particle size

2.4. Determination of ash yield

The wood-coconut-kaolin (WCK) mixture (2 g) with varying particle size as generated by the software was placed in 50 ml crucible and oven-dried at 105 ^{o}C to constant weight. The WCK mixture sample were further allowed to burn in an ash burner until no smoke or flame appeared and the resulting products were heated in a muffle furnace at 900 ^{o}C for 8 hr before being cooled in desiccator and then reweighed according to the ASTME1755-01. The oven-dry weight (ODW) and percentage ash yield obtained for each run were calculated according to Equations 5 and 6.

$$ODW = \frac{\text{Weight in dry air} \times \% \text{ total weight}}{100} \quad (5)$$

$$ODW = \frac{\text{Weight in dry air} \times \% \text{ total weight}}{100} \quad (6)$$

2.5. Artificial neural network modelling of the combustion parameters

The input parameters (wood, coconut *the the the*, kaolin mixture as well as particle size) and output parameter (ash yield) of the combustion process as indicated on the experimental design (Table 2) were modelled using Artificial Neural Network (ANN) (Figure 1). The accuracy of the network requires selection of optimal architecture which includes the number of neurons hidden layers, and the learning rate that minimizes the Root Mean Square error (RMSE). The 23 data points obtained from design of experiment were divided into a training data and testing data sets in the relative proportion (9:1). This implies that for every 10 selected data points, 9 points are used for the training while one is utilized for testing. Training set are data points utilized for training ANN model based on the selected training algorithm and ANN architecture while testing set is utilized to test the accuracy of the developed model. Testing set is unknown to the model during training. The training data is used by Levenberg Marquadrt algorithm in order to regulate the synaptic weight and the testing data is used to halt training at the verge of over fitting (Ryad et al., 2019). Different network architectures were tested by varying the number of neurons from 3 to 20 at two different learning rate ƛ = 0.05 and 0.1.

2.6. Ash characterization

The ash yield obtained for each experimental run was characterized using X-ray Diffraction (XRD) machine to determine its chemical compositions. A small amount of the WCK mixture ashes were put on a sample holder and measured by a Siemens D500 diffractometer, using Cu Kα radiation at 30 mA and 40 kV with step scanning in the range of 20° to 60° 2θ at a rate of 1° 2θ/min (step width 0.05° 2θ for 3 s). Afterwards, the obtained XRD diffractograms were evaluated applying the X'pert Highscore and OriginPro.8.5 software.

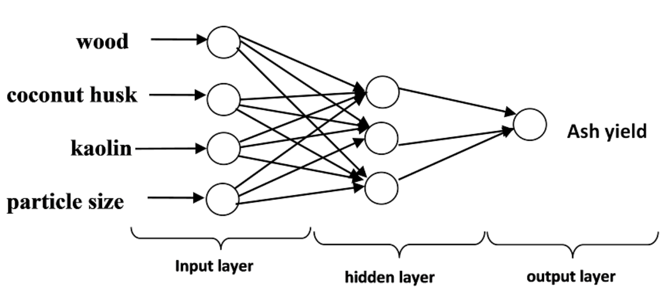

Figure 1: The schematic illustration of artificial neural network for wood-coconut husk–kaolin mixture and particle size

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2.7. Verification of estimated data

Mean Square Error (MSE), Root Mean Square Error (RMSE) as well as coefficients of determination (R^2) were used to evaluate ANN which are common measures for model predictability and are determined from Equations 7-9. The network having minimum RMSE and maximum R^2 is considered as the best and R^2 value which is closer to value of 1.0, indicate that the model is better fit to the actual (Eriola and Ezekiel, 2015).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_{ai})^2 \quad (7)$$

$$RMSE = \sqrt{MSE} \quad (8)$$

$$R^2 = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - y_{ai})^2}{(y_{ai} - y_{mi})^2} \quad (9)$$

where ; n is the number of point, $y_i y_i$ is the predicted value obtained from neural network, y_{ai} is the actual value and y_{mi} is the average of actual value.

3. Results and discussion

3.1. Optimization of ash yield by D-Optimal and ANN

The results of the twenty three runs using D-optimal design under the Combined Methodology for the mixture, factor (particle size) study and the ash yield response indicated percentage ash yield ranging from 2.50 % to 22.34 % (Table 2).

Experimental Run 22 with 85 % wood, 5 % coconut husk, 10 % kaolin and 2.5 mm particle size gave the minimum ash yield (2.50%). This may be due to the high wood composition in the blend, as suggested by Blas et al (2014) that wood has relatively low ash deposition when combusted. Experimental Run 21 with 50 % wood, 45 % coconut husk, 5 % kaolin and 1.75 mm particle size gave the ash yield (9.82 %). However, experimental Run 9 with 5 % wood, 95 % coconut husk, 0 % kaolin and 1

Table 2: Results of responses from experimental data for both D Optimal and ANN

	Components			Factor	Responses		
Runs	Wood (%)	Coconut husk (%)	Kaolin (%)	Particle s ize (mm)	Actual Value (%)	D optimal Predicted Values (%)	ANN Predicted Values (%)
1	85.00	5.00	10.00	1.00	5.45	6.29	5.50
2	5.00	94.00	1.00	1.00	13.71	15.37	13.62
3	94.00	5.00	1.00	1.00	3.63	3.69	3.62
4	5.00	85.00	10.00	4.00	13.54	11.41	13.52
5	5.00	94.00	1.00	4.00	3.75	4.65	3.74
6	94.00	5.00	1.00	2.50	2.50	3.19	2.50
7	95.00	5.00	0.00	4.00	11.15	7.94	11.00
8	49.50	49.50	1.00	4.00	5.46	8.42	5.41
9	5.00	95.00	0.00	1.00	22.34	20.72	22.10
10	80.00	15.00	5.00	2.50	2.96	3.23	2.90
11	5.00	85.00	10.00	2.50	9.50	9.32	9.47
12	85.00	5.00	10.00	4.00	15.00	14.37	14.00
13	5.00	94.00	1.00	1.75	3.03	2.21	3.00
14	49.50	49.50	1.00	1.00	8.81	8.53	8.21
15	85.00	5.00	10.00	2.50	10.66	11.08	11.56
16	47.25	47.25	5.50	2.50	7.62	6.21	7.10
17	5.00	89.50	5.50	1.00	18.45	18.04	18.04
18	89.50	5.00	5.50	4.00	8.21	11.15	8.90
19	26.13	66.13	7.75	1.75	12.31	7.74	12.10
20	26.13	66.13	7.75	3.25	4.76	7.74	4.50
21	50.00	45.00	5.00	1.75	9.82	8.73	9.10
22	85.00	5.00	10.00	2.50	2.50	2.61	2.49
23	5.00	85.00	10.00	4.00	11.00	12.10	11.12

mm particle size gave the highest ash yield (22.34 %). Thus indicating the importance of additives (kaolin) in the reduction of ash in biomass subjected to combustion process (Kareem et al., 2018). Further, it suggests that the biomass mixture composition (Run 9) is inefficient for energy generation and may further trigger corrosion problems in the boiler as a result of its high ash content (Katsuya and Ichiro, 2011; Kareem et al., 2018).

The quadratic model generated by the software (DOE) for accurate prediction of ash yield for the mixture of wood, coconut husk and kaolin with varying particle sizes in terms of coded factors is expressed in Equation 10.

$$Ash\ yield = +0.18X_1 + 36.21X_2 + 50.26X_3 - 0.62X_1X_4 - 24.85X_2X_4 + 30.62X_3X_4 + 0.61X_1X_4{}^2 + 4.18X_2X_4{}^2 - 5.87X_3X_4{}^2 \quad (10)$$

where: X_1= wood, X_2= coconut husk, X_3 = kaolin and X_4= particle sizes.

Test of significance of the coefficients was investigated using Probability (p) values and residual least-squares errors. The statistical analysis of the quadratic model and coefficients in term of real and actual factors are presented in Table 3 and 4, respectively. The generated model coefficients were highly adequate in fitting the experimental results at 0.0001 probability for ash yield. Value of R^2 and adjusted R^2 of the model were found to be 0.8825 and 0.8153. The relatively high values of R^2 and adjusted R^2 indicated that the coefficients were accurately determined for the model (Eriola & Ezekiel, 2015).

The F-value of 13.14 generated for the model indicate the significance nature of the model and such as has about

Table 3: Statistical analyses of quadratic model

Source	Sum of squares	Df	Mean Square	F Value	P Value Prob> F
Model	545.61	8	68.20	13.14	< 0.0001*
Linear Mixture	208.47	2	104.24	20.09	< 0.0001*
X_1X_4	0.069	5	0.069	0.013	0.9095
X_2X_4	128.02	1	128.02	24.67	0.0002
X_3X_4	1.45	1	1.45	0.28	0.6059
$X_1X_4^2$	1.75	1	1.75	0.34	0.5701
$X_2X_4^2$	94.05	1	94.05	18.12	0.0008*
$X_3X_4^2$	1.38	14	1.38	0.27	0.6143
Residual	72.65	22	5.19		
Cor Total	618.26				

*Significant at $p < 0.5$

Table 4: Coefficients in terms of real components and actual factors

Component	C_e	df	S_e	95%Cl Low	95%Cl High	VIF
X_1- wood	0.18	1	5.66	-11.97	12.33	47.04
X_2-cocont husk	36.21	1	5.32	24.79	47.63	46.38
X_3- kaolin	50.26	1	62.38	-83.54	184.05	70.57
X_1X_4	-0.62	1	5.34	-12.06	10.83	352.5
X_2X_4	-24.85	1	5.00	-35.57	-14.12	265.1
X_3X_4	30.62	1	58.01	-93.80	155.03	458.0
$X_1X_4^2$	0.61	1	1.04	-1.63	2.84	172.7
$X_2X_4^2$	4.18	1	0.98	2.07	6.29	116.9
$X_3X_4^2$	-5.87	1	11.39	-30.29	18.55	208.7

(a)

Ce: coefficient estimate, df: degree of freedom, Se: standad error, VIF: variance inflation factor

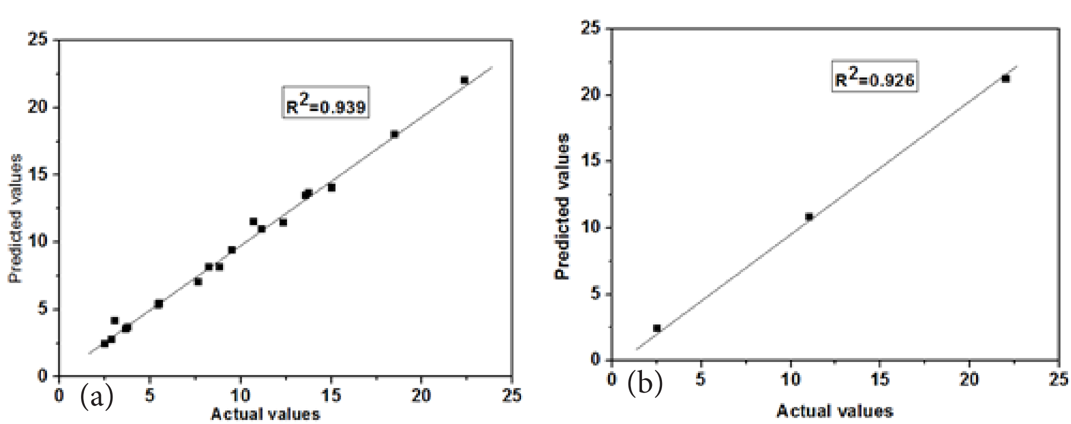

Figure 2: Parity plots of predicted values versus actual value for (a) training set (b) testing set

0.01% chances of occurrence due to noise. Model terms with prob > F values less than 0.05 are considered to be significant (Farombi et al., 2018), thus the terms X_2X_4 and $X_2X_4^2$ are the significant models terms in this study. It may suggest that the coconut husk (X_2) was most sensitive to change in particle sizes X_4 in the mixture. The adequate precision of the statistical analysis of the data obtained is expected to be grater than 4, for it to be suitable as adequate signal with respect to the noise and the value of 13.667 indicate a good measure.

The 23 data points obtained from experimental design were divided into two groups; the training set (90%) and testing set (10%). The minimum RMSE was obtained for learning rate of 0.05 and 14 neurons in the hidden layer. The performance of network did not change significantly with lower number of neurons in the hidden layer. Scatter plots of predicted ratio against the actual ratio were in good agreement. The R^2 obtained for training and testing data set are 0.939 and 0.926 respectively, while the accuracy of the model is within error bounds of ± 0.24 for the ash yield. Thus, the coefficient of determination obtained by the use of ANN is higher than those obtained in D-Optimal Design.

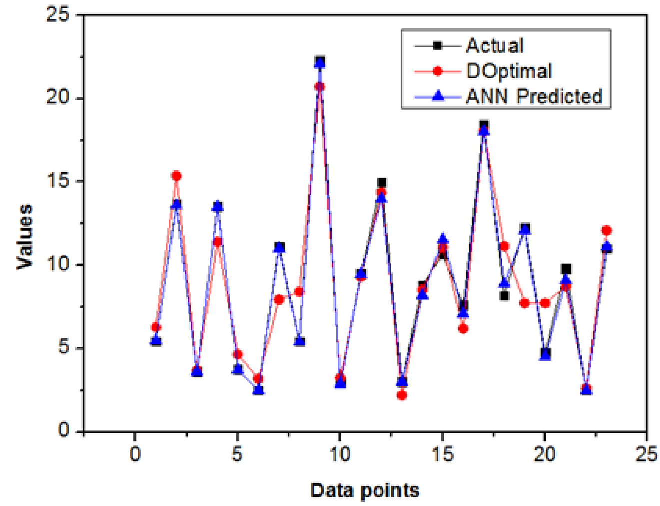

Figure 3: Actual values of the ash yield, D optimal and ANN predicted values

The trends of the actual value of the ash yield as well as the predicted values from the D Optimal Design and ANN are illustrated in Figure 3. For every nine (9th) data point selected for the training the (10th) one serves as the testing. These data of runs 1, 10 and 19 were the test results while the remaining ones are training data set.

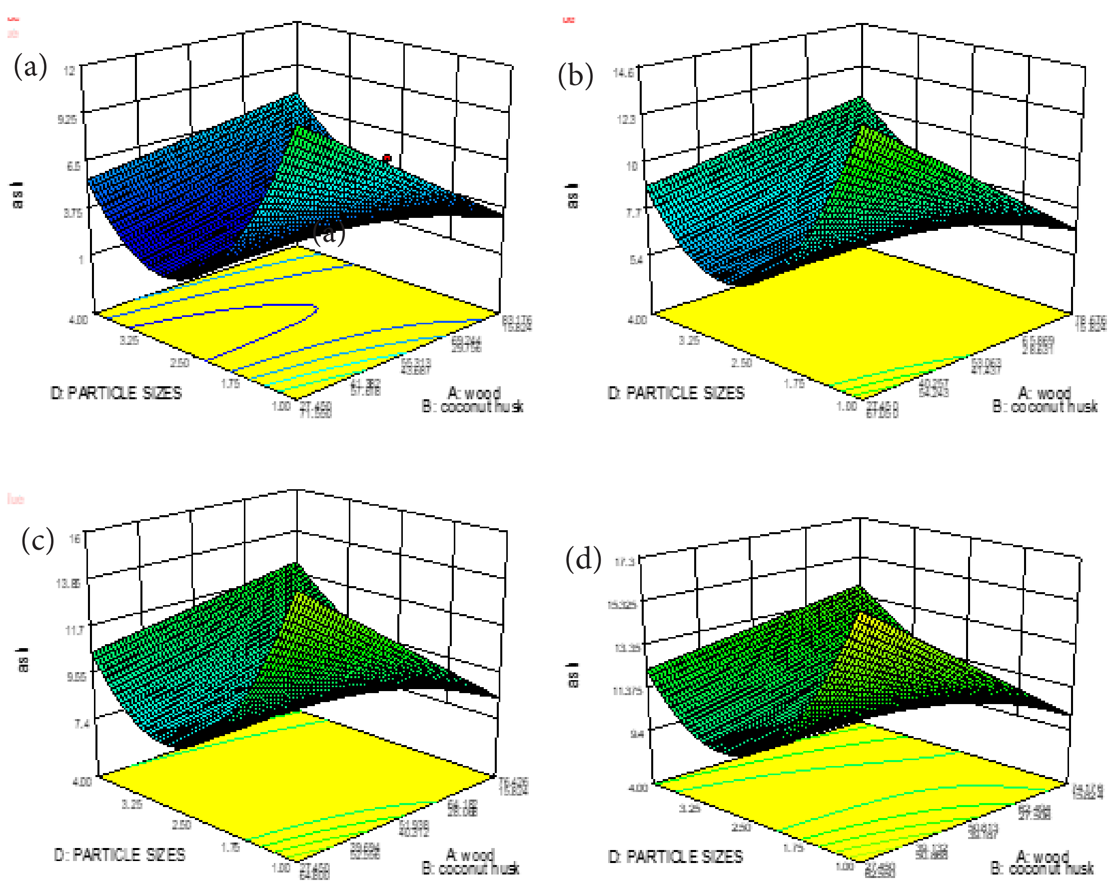

Figure 4: 3D response surface plots representing the interaction of particle size and wood coconut husk mixture with (a) 10 % kaolin (b) 7.5% kaolin (c) 5 % kaolin and (d) 1 % kaolin on ash yield

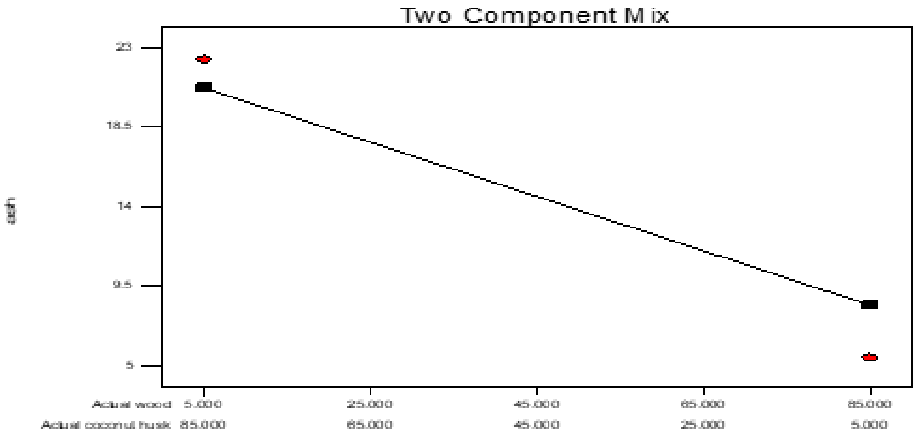

Figure 5: illustrate the interaction of wood and coconut husk on the ash yield while keeping particle size at 2.5 mm and at 10% kaolin

3.2. Interactive effect of the process parameters on response

The outcome expressed in 3D response surface plots (Figure 4a-d) shows the interaction of wood-coconut husk mixture and particle sizes on the ash yield at different percentages (10%, 7.5 %, 5.5 % and 1 %) of kaolin respectively. The convex nature is signals that the ash yield was minimized (Kareem et al., 2018) and the curve plots indicate a quadratic interaction. The two components mix graph (Figure 5) illustrates the interaction of any two components on the ash yield while keeping other components at constant. The kaolin addition on wood -coconut husk mixture has a significant impact on the ash yield. It is apparent that the percentage ash yield increased as the percentage composition of coconut husk increased and decreased as the percentage composition of wood increased. This observation was in line with the work of Blas, (2014) that wood has relatively low ash deposition when combusted.

3.3. Characterization of ash yield after combustion of wood, coconut husk and kaolin mixtures

The XRD analysis of the ash yield to detect the mineral phase compounds formed was carried out to confirm the interaction between wood, coconut husk and kaolin mixtures. The three samples obtained as Run 22, Run 21 and Run 9 based on their (minimum, average and the maximum) percentages of ash yield from experimental design response shows that the XRD patterns was similar being mainly amorphous with several major crystalline peaks superimposing from the amorphous areas. Compounds such as SiO_2, $KAlSi_3O_8$, $Na_{2.43}$ $A_{10.19}$ (PO_4) and KSCN were identified to be major crystalline compounds based on the intensity of their peaks (Figure 6a). The diffraction peaks identified in ash yield for Run 22 and 21 (Figure 6a&b) clearly shows the presence of SiO_2, NaN_3, ClO_3F, Al, $KAlSi_3O_8$ and $K_{7.7}$ $Na_{0.3}$ $(Al\ Si\ O_4)_6(ClO_4)_2$. The ash yield from Run 9 was rich in SiO_2, SiS_2, $H_2Si_2O_52H_2O$, and KHS (Figure 6c). Peak attributed to sanidine ($KAlSiO_3$) was observed when 10 % and 5% kaolin was added to the solid fuel mixture respectively. The presence of sanidine and other risk compound such as K, Al, and Si suggests interaction of potassium-kaolin reaction (Steenari et al., 2009; Yanqing et al., 2015; Yingzu and Kaidi, 2020). This could inhibit ash production rate and prevent the release of KCl. The presence of sanidine and other related potassium aluminate (Figure 6c) that could raise the melting temperature of ash in the fuel, all the compound shown are not alkaline silicate, this could probably due to absence of kaolin in the fuel mixture (Sebastien et al., 2017). Appearance of merwnite $(Ca_3MgSiO_4)_2$ and gelhenite ($Ca_2Al_2SiO_7$) was found in the XRD pattern of *Albizia zygia* wood dust fly ash and are generally suitable for land application, but in boilers the fly ash lead to increase in pollutant formation along with rapid buildup of ash deposition on the surfaces of riser components, reduced efficiency and power cost (Aaron et al., 2019). The XRD spectrum of coconut husk without additive was also investigated (Glarborg et al., 2011). His findings indicated that peak characteristics of potassium oxide can be observed in diffractogram and makes combustion of coconut husk ash more prone to slagging and corrosion formation.

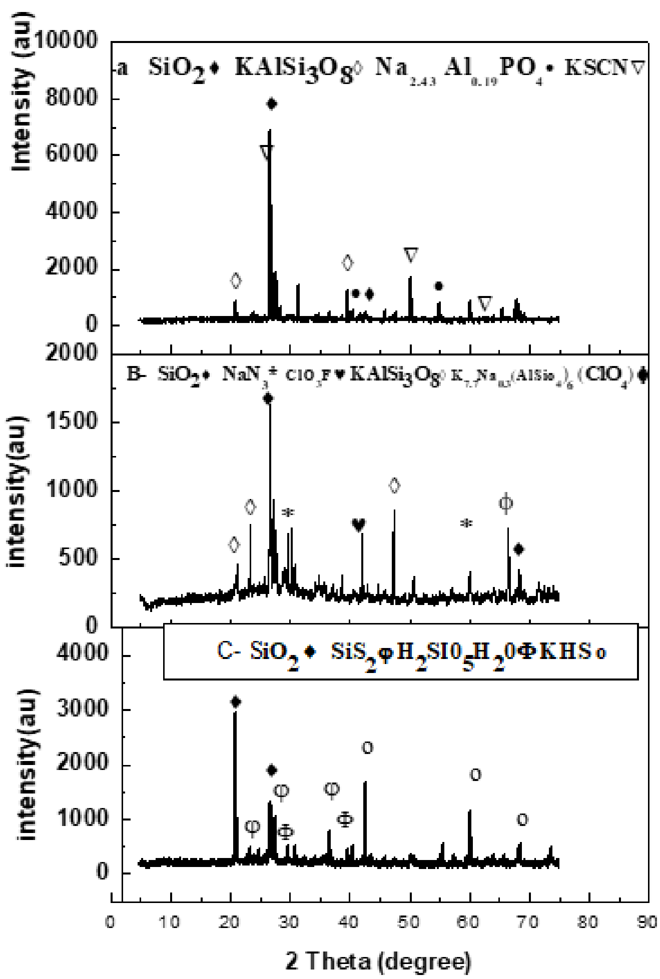

Figure 6: XRD patterns of the combustion of (wood, coconut husk and kaolin burned ratio) on the ash yield (a) Run 22, (85 %-5 %-10 %) (B) Run 21 (50 %-45 %-5 %) (C) Run 9 (5 %-95 %-0 %)

4. Conclusion

In this study the influence of kaolin additive and combustion characteristics of *Albizia zygia* wood and coconut husk mixture on ash yield was investigated. Results from our experimental and ANN models revealed that ash depositions are influenced by both the biomass contents and additive. The optimal values established for the ash yield were wood (85 %), coconut husk (5.0 %), kaolin (10 %) and particle sizes (2.50 mm) respectively. The regression coefficient (R2) of the model quadratic equation obtained for the process is 0.8825 while the adjusted R2 is 0.8153. The ANN (R2) values for the model predictions were 0.939 for the training set and 0.926 for the testing set respectively. The appearance of sanidine (KAlSiO3) in the wood-coconut additive ash prevented release of potassium chloride which has the ability to increase ash deposition and corrosion in steam boiler.

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