



# Optimization of Ash Yield from Bicomposite Biomass (*Terminalia catappa* and *Chrysophyllum albidum*) Seed Barks with Additive upon Combustion

Ebenezer Olujimi, Dada<sup>1</sup> Uriel Olamilekan, Awe-Obe<sup>1,2</sup>,  
Kamoru Olufemi, Oladosu<sup>3</sup>, Abass Olanrewaju, Alade<sup>1,2,4\*</sup>  
and Tinuade Jolaade, Afolabi<sup>1,2</sup>

<sup>1</sup>Department of Chemical Engineering, Ladoko Akintola University of Technology, Ogbomoso, Nigeria.

<sup>2</sup>Bioenvironmental, Water and Engineering Research Group (BWERG), Ladoko Akintola University of Technology, Ogbomoso, Nigeria.

<sup>3</sup>Mechanical Engineering Department, Kwara State University, Malete, Kwara State, Nigeria.

<sup>4</sup>Science and Engineering Research Group (SAERG), Ladoko Akintola University of Technology Ogbomoso, Nigeria.

## Authors' contributions

This work was carried out in collaboration among all authors. Authors EOD and AOA designed the study, performed the statistical analysis, and wrote the protocol and author UOAO wrote the first draft of the manuscript. Authors TJA and KOO managed the analyses of the study. Author UOAO managed the literature searches. All authors read and approved the final manuscript.

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## ABSTRACT

The ash yield from the combustion of a mixture of Africa star apple and tropical almond seeds shells (bicomposite biomass) with ammonium dihydrogen phosphate as an additive in a furnace was optimized using I-Optimal Design under the Combined Methodology of the Design Expert Software. The data obtained were analysed statistically using Analysis of Variance (ANOVA), Artificial Neural

Network (ANN) for the prediction of ash yield and Principal Component Analysis (PCA) to determine the coefficient of determination ( $R^2$ ) between variables. Proximate analysis was used to evaluate Moisture Content (MC), Fixed Carbon Content (FCC), and Volatile Matter (VM) values while the Higher Heating Value (HHV) of the mixtures that gave the highest and lowest ash yields was evaluated numerically. The optimum conditions of process variables for the compositions of tropical almond, African star apple, and ammonium dihydrogen phosphate, as well as the temperature, were 30%, 60%, 10% and 704 °C, respectively leading to a minimum ash yield of 24.8%. The mathematical models for the ash using the I-optimal design indicate a good fit to the Quadratic model with a  $R^2$  of 0.9999. The ANN model agreed significantly with the experimental results with an  $R^2$  of 0.9939. The VM, FCC, MC, AC and HHV of the highest ash yield were 11.00%, 2.34%, 3.20%, 33.80% and 4487.747  $KJ/kg$ , respectively. The study established the suitability of optimisation tool to develop solid fuel mixtures for possible use in grate furnaces and its efficiencies.

**Keywords:** Ash yield; biomass; I-optimal design; optimization; solid fuel.

## 1. INTRODUCTION

Biomass has been identified as one of the renewable energy resources to replace traditional fossil fuels in the aspect of carbon credit [1-2]. Agricultural waste and herbaceous biomass are not limited and can be made use of both in small domestic stoves and large-scale power industries. However, raw biomasses may not be directly suitable for thermal conversion, as a result of low heating values, low energy volumes, and difficulty in storage and transportation [1-2]. However, biomass fuels are rich in alkali metals which when used in biomass combustion systems show some negative influences causing alkali-related operational problems, including fouling, sintering, superheater corrosion, and bed agglomeration [3]. Problems such as slagging, fouling, and surface corrosion of heat exchange equipment are often caused by alkali metals during biomass combustion, which prevent the clean utilization of biomass energy. Comparing other methods used in solving ash-related problems, the addition of a mineral-based additive is an important solution due to its easy operation. Addition of the additives during the densification process in the conversion mechanism in the pyrolysis makes the ash fusion phenomenon improve effectively. Contributing to the formation of high temperature melting calcium potassium phosphate, phosphorous tends to dominate over silicon elements for alkali capture [1-2]. In biomass, Potassium (K) is the dominating type of alkali metal because, in the growth of plants, it is the essential element [3]. Phosphorus-rich additives have positive effects on potassium held in ash and could alleviate the ash melting problems effectively.

During the burning of biomass in air, potassium interacts in complex transformation reactions

together with other ash-forming elements that may form potassium salts, silicates, and phosphates residue in the ash and are released into the gas phase through a sublimation process of KCL [3]. Previous studies have given good guidance and solution to solving ash-related issues that are caused by alkali metals through the addition of different phosphate-based additives [4]. Often, in previous studies, little attention has been devoted to the effect of phosphorus on the migration and transformation of alkali metals. So, this brings about the study in controlling mechanism of ammonium phosphate-based additives on migration and transformation of alkali metals being studied [4].

*Chrysophyllum albidum* (African star apple) is a tropical fruit widely distributed in West, East and Central Africa. It belongs to the family of *Sapotaceae* and is widely demanded because of its sweet succulent fruits and medicinal value [5-6]. African star apple fruit is a seasonal fruit and is usually available from December of a year to April of another year. It is oval with pale orange thick skin and contains about five seeds. The seeds are characterised with semi-hard shells and they are often discarded indiscriminately in the environment coupled with the fruits' high (30%) postharvest losses. Thus, a huge amount of biomass is generated as solid wastes from this fruit annually [5].

The *Terminalia catappa* (Tropical almond) is a large tree often characterised by spreading branches and It is widely planted throughout the tropics, especially along sandy seashores, for shade, ornamental purposes, and edible nuts. The tropical almond is a medium to large tree of 25–40 m (82–130 ft) in height and at maturity, the trunk attains a diameter of about 50–150 cm (20–60 in). Between one and five fruits, which is a sessile, laterally compressed, ovoid to ovate,

smooth-skinned drupe, usually develop on the basal part of the flower spike. The tasty kernels or nuts of tropical almonds have traditionally been incorporated, albeit in modest quantities, into the diet of people in coastal areas throughout much of the Asia-Pacific region. The nuts may be consumed fresh shortly after extraction from the shell or else preserved by smoking and consumed up to a year later. The fibrous and tough shells are often discarded at the bottom of the parent tree in most places and litter the environment. The two agrowastes were selected in this study for their potentials as renewable solid fuel with a less adverse effect on the combustion system Ammonium dihydrogen phosphate (ADP) is part of a large family of crystals with  $MH_2XO_4$  (where, M=K, Na,  $NH_4^+$ , X=As, P) [7]. It is also known as mono-ammonium phosphate. It is used widely in industries such as flame retardant, fertilizers, feed, food, and water treatment [8].

Artificial neural networks (ANN) models use a non-physical modeling approach that correlates the input and output data to form a process

prediction model. ANN is a universal function approximator that can approximate any continuous function to an arbitrary precision even without a priori knowledge on the structure of the function that is approximated [9]. ANN models have proven their potential in the prediction of various process factors in energy-related processes [10,11,12,13]. ANN has to be designed and implemented in a way that the set of input data results into a desired output (either direct or by using a relaxation process). ANN-based solutions have provided excellent results/insides into very complex problems in forecasting, data-mining, task scheduling, or optimised resource allocation problems. On the other hand, Principal component analysis (PCA) is a multivariate technique that analyzes a data set in which observations are described by several inter-correlated quantitative dependent variables. Its primary target is to extract the important information, represent it as a set of new orthogonal variables called principal components, and then display the pattern of similarity of the observations and the variables as points, graphically [14].



**Fig. 1. (a) African Star Apple fruit (b) African Star Apple seed (c) Tropical Almond fruit and (d) Ammonium dihydrogen phosphate salt**

The research aimed to optimise ash yield from the combustion of bicomposite biomass materials (Africa star apple and tropical almond seeds) using ammonium di-hydrogen phosphate as an additive in a furnace. The specific objectives were optimization of ash yield from the combustion of bicomposite biomass (Tropical Almond and African Star Apple) mixture, Modeling ash yield using Artificial Neural Network (ANN) and Principal Component Analysis (PCA) as well as characterization and estimation of the higher heating value of the biomass materials using proximate analysis.

## 2. METHODOLOGY

### 2.1 Materials Processing

The Tropical almond and the African star apple seeds that were used in this study were obtained from local markets in Ogbomoso, Oyo State, Nigeria. These materials were washed severally with water and thoroughly rinsed with distilled water to remove any soluble materials attached to the biomass. The materials were kept in open trays for several days to get air-dried samples and to avoid the biological decay of wet samples. The air-dried samples were milled with a special shredder designed for leafy materials and then sieved to pass through a screen of 250 µm openings. The milled and sieved samples were stored in air-tight sample bottles to avoid further interaction with air.

### 2.2 Experimental Design

The I-optimal Design under Combined Methodology embedded in the design expert software (12) was employed to optimize the mixture and process factors. The minimum and the maximum level of the components (tropical almond, *Chrysophyllum albidium* and ammonium dihydrogen phosphate) set for the software are in the range of 0-100% (Table 1). The experimental design generated twenty-two (22) experimental runs. These were used to investigate the effects of temperature on the mixture components of the ash to be produced.

### 2.3 Determination of Ash Yield in the Mixture of Tropical Almond, *Chrysophyllum Albidium* and Ammonium Dihydrogen Phosphate

The tropical almond, *Chrysophyllum albidium* and ammonium dihydrogen phosphate mixtures

were ashed according to the ASTM E1755-01 (ASTM, 2005). The sample mixture (5 g) was put in crucibles which were placed in the muffle furnace at the preset and selected temperatures (600-900 °C) for 2 h. The crucibles were then retrieved and placed in the desiccators to cool for 1 h. The Oven-Dry-Weight (ODW) and the percentage ash content were determined according to Eqns. 1 and 2, respectively. The ash yield obtained for each run was inputted into the software for further statistical analysis such as analysis of variance (ANOVA) and assessment of the quality of fit of the models generated using the tool in the Design-Expert Software environment [15-16].

$$ODW = \frac{Weight_{air-dried\ sample} \times 100}{Total\ Sample} \quad (1)$$

$$\%Ash = \frac{Weight_{crucible+ash} - Weight_{crucible}}{ODW} \quad (2)$$

### 2.4 Neural Network Modelling (ANN)

Neural Network Toolbox V15.0 of MATLAB mathematical software was used to predict the ash yield of biomass during the combustion process. The process was identified in this study to be significantly influenced by a main process variable which is temperature. Multiple Layer Perceptron (MLP) based on feed-forward ANN was applied to build the predictive model for the pilot plant. The network consists of four (4) input layers, six hidden layers, and one output layer. The inputs for the network are flamboyant pod, groundnut shell, kaolin, and temperature. Output is the percentage ash yield.

### 2.5 Principal Component Analysis

Data were entered into MATLAB (version 15) and a PCA was conducted on the 20 runs, using a direct (oblique) rotation. The aim was to obtain a parsimonious solution by explaining the variation in the original data set using a few underlying components (Tabachnick & Fidell 2014). Using pairwise deletion for missing data, item-to-subject ratios met the recommendations for sample size. Reliability tests of Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and communality values justified the use of PCA.

### 2.6 Determination of Biomass Mixture Properties

The properties of tropical almond, *Chrysophyllum albidium* and ammonium dihydrogen phosphate

mixtures that were determined according to ASTM (2007) are moisture content, volatile matter, fixed carbon content and Heating value was estimated.

### 2.6.1 Percentage of volatile matters (VM)

The crucible was oven-dried to constant weight, filled 5 g of the mixture and heated in the muffle furnace at a temperature (600 - 800 °C ) according to the experimental design, for 60 mins. the crucible and its content were cooled in the desiccator and then weighed to determine its volatile matter according to Eqn 3.

$$\% \text{ VM} = \frac{X_0 - X}{X_0} \times 100 \quad (3)$$

Where  $X_0$  is the sample weight after oven-drying and  $X$  is the sample weight after heating in the furnace.

### 2.6.2 Determination of moisture content

The crucible was placed in the muffle furnace at 600 °C for 60 mins before placing it in a desiccator for 15 mins, The dried crucible weight was noted before being filled with 5 g of the sample mixtures and the sample weight in addition to the weight of the crucible was recorded. The crucible that contained the sample dried in the furnace at temperatures of 600-800 °C for 2 days. The crucible was put in a desiccator for 20 min and its weight was recorded. The expression for moisture contents is given by Equation 4.

$$\% \text{ MC} = \frac{C_1 - C_2}{C_1 - C_0} \times 100 \quad (4)$$

where;  $C_0$  is the crucible weight (g),  $C_1$  is the crucible weight and sample before dry in the oven (g); and  $C_2$  is the crucible weight and sample after drying

### 2.6.3 Determination of ash content

The crucible with the sample in it was placed into the muffle furnace and gradually heated to 600-800°C and kept inside the furnace for a period of 1 h. The crucible was removed and put in a

desiccator to cool to room temperature. It was then weighed and the difference in weight is the ash content, determined using Equation 5.

$$\begin{aligned} \text{weight of ash} &= (\text{weight of crucible and ash}) \\ &\quad - \text{weight of crucible} \\ \% \text{ ash} &= \left( \frac{\text{weight of ash}}{\text{original sample}} \right) \times 100 \quad (5) \end{aligned}$$

### 2.6.4 Determination of carbon content

Fixed carbon content was calculated as the difference between 100 and the sum of volatile matter and ash contents. The expression for fixed carbon contents is given by Eqn 6.

$$\% \text{ FC} = 100 - (\text{VM} + \text{A}) \quad (6)$$

where; VM is the percentage of volatile matter (%), A is the percentage of ash

### 2.6.5 Determination of heating value

This is the calorific value of the heat generated by a given sample. Good material for burning must possess a high heating value. The heating value was calculated using the formula.

$$HV = 2.326 (147.6C + 144V) \text{ KJ/kg} \quad (7)$$

Where: HV = heating value (kJ/kg), C = percentage fixed carbon (%), V = percentage volatile matter (%)

### 2.6.6 Determination of volatility

The sample was placed on the evaporating dish after the moisture content analysis, then transferred into the crucible and placed in a muffle furnace at 550°C for 30 mins. The dish and sample were cooled in a desiccator and weighed. To calculate the total volatile contents concentration with the equation.

$$v = (R - A) \frac{100}{\text{sample weight}} \quad (8)$$

Where, R: the weight of the crucible and sample before ignition and A: the weight of the crucible after ignition.

**Table 1. Components, factor and their levels experimental design**

Component	Name	Minimum	Maximum
A	<i>Chrysophyllum Albidium</i>	30	50
B	<i>Terminalia Catappa</i>	40	60
C	Ammonium di-hydrogen phosphate	5	10

### 3. RESULTS AND DISCUSSION

#### 3.1 Ash Yield

The optimization results of the mixture of Tropical Almond, African Star Apple and Ammonium Di-hydrogen Phosphate at varying temperatures based on the I-Optimal Design (Table 2), showed that the ash yield ranged between 24.8% and 37.6% for twenty-two (22) runs. Experimental Run 19 [African star apple (38%), Tropical Almond (54%), ammonium di-hydrogen phosphate (8%), and temperature (600 °C)] gave the maximum (33.8%) ash yield, experimental run 11 [African star apple (45%), Tropical Almond (50%), ammonium di-hydrogen phosphate (5%), and temperature (747 °C)] gave average (28.0%) ash yield while Experimental run 7 [African star apple (37%), Tropical almond (56%), ammonium di-hydrogen phosphate (5%) and temperature (752 °C)] gave minimum (24.8%) ash yield.

#### 3.1 Model Formulation and Statistical Analysis

The quadratic models generated by the software (DOE) for accurate prediction of ash yield for the

mixture of Tropical Almond, African Star Apple, Ammonium Di-hydrogen Phosphate, at various particle sizes and temperatures in terms of coded factors are expressed in Equation 9. The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. By default, the high levels of the mixture components and process factors are coded as +1, the low levels of the mixture components are coded as 0, and the low levels of the process factors are coded as -1. The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients

$$\begin{aligned} \text{Ash yield} = & 55.45A + 40.65B + 259.99C + \\ & 82.58AB - 409.58AC + 29.93AD - \\ & 377.15BC + 2.33BD + 9.29CD + 493.76ABC - \\ & 105.95ABD - 285.08ACD - 23.26BCD - \\ & 78.37 AD^2 - 42.45BD^2 - 408.35CD^2 + \\ & 868.04ABCD + 298.36ABD^2 + \\ & 1019.58ACD^2 + 807.36BCD^2 - \\ & 2066.5ABCD^2 \end{aligned} \quad (9)$$

Where; A= *Chrysophyllum Albidium*, B= *Terminalia Catappa*, C= Ammonium Dihydrogen Phosphate.

Table 2. Result of design experimental run for mixture, factor and ash yield response

Run	Component			Factor	Response
	A: <i>Chrysophyllum albidium</i>	B: <i>Terminalia catappa</i>	C: Ammonium Di-hydrogen Phosphate	D: Temperature (K)	Ash Yield (%)
1	35	60	5	600	37.6
2	43	47	10	600	34.4
3	50	45	5	795	25.2
4	34	56	10	752	29.4
5	44	48	8	800	29.6
6	35	60	5	702	30.2
7	37	58	5	800	24.8
8	33	60	7	653	27.8
9	31	60	9	800	30.6
10	39	51	10	800	29.4
11	45	50	5	747	28.0
12	50	41	9	696	33.6
13	50	45	5	646	28.4
14	47	48	5	600	35.2
15	31	60	10	704	24.8
16	30	60	10	605	36.4
17	39	54	7	700	26.2
18	50	40	10	790	28.2
19	38	54	8	600	33.8
20	40	50	10	650	29.0
21	41	49	10	699	30.4
22	50	42	8	600	32.8

### 3.2 Analysis of variance (ANOVA) for Ash yield

Statistical analysis embedded in DOE software was used to evaluate the analysis of variance. Numerical optimization of the analysis of variance of the data obtained for ash yield was presented in Table 3. Inference for linear mixtures uses Type I sums of squares, mixture Component coding is L\_Pseudo. The Sum of squares is Type III – Partial. The Model F-value of 872.25 implies the model is significant. There is only a 2.67% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. In this case, A, B, C, AB, AC, AD, BC, ABD, AD<sup>2</sup>, BD<sup>2</sup>, CD<sup>2</sup>, ABCD, ABD<sup>2</sup>, ACD<sup>2</sup>, BCD<sup>2</sup>, and ABCD<sup>2</sup> are significant model terms. Values greater than 0.1000 indicate the model terms are not significant.

### 3.3 Model Graph for Response on the Interactive Effect of the Process Parameters

A circular contour of response surfaces indicates that the interaction between the corresponding variables is negligible. An elliptical or saddle nature of the contour plots indicates that the interaction between the corresponding variables is significant. The three-dimensional (3D) model graphs for the ash yield are based on the process parameters illustrated in Fig. 2. The curvature natures of the 3D surface plots show mutual interactions among the mixtures (Tropical Almond, African Star Apple, and Additives) investigated as they affect the ash yield. The outcomes validate that the quadratic equation is appropriate [15-16].

Normal Plot of Residuals (Fig. 3a) the normal probability plot of the residuals indicates whether the residuals follow a normal distribution, thus a straight line indicates good accuracy of the regression model as shown, (Figs 3a) is a plot of Normal is compared with the Externally Studentized Residuals (Figs 3b), it helps to explain the degree of fit of compositions of different runs generated by the software. Residual vs predicted (Figs 3c) shows the plot of the residuals versus the ascending predicted response values. It tests the assumption of constant variance. Predicted vs actual (Figs 3d) is a plot of the residuals versus the experimental run order. It explains the variations between the predicted and the actual values, runs fall on the straight line with no scattered. Both figures check for lurking variables that may have influenced the response during the experiment. The randomized scatter of the plot shows the accuracy and consistency of the model. Contour plot of the ratio of African star apple, Tropical almond and Ammonium di-hydrogen phosphate was given by DOE, and it shows the degree of the relationships of African star apple, Tropical almond and Ammonium di-hydrogen phosphate against Ash yield.

Adeq Precision measures the signal-to-noise ratio and a ratio greater than 4 is required [17], thus the ratio of 102.243 (Table 4) indicates an adequate signal and this implies that the model can be used to navigate the design space. Negative Adjusted R<sup>2</sup> appears when the Residual sum of squares approaches the total sum of squares and it means insignificance of explanatory variables, although the results may be improved with the increase in sample size.

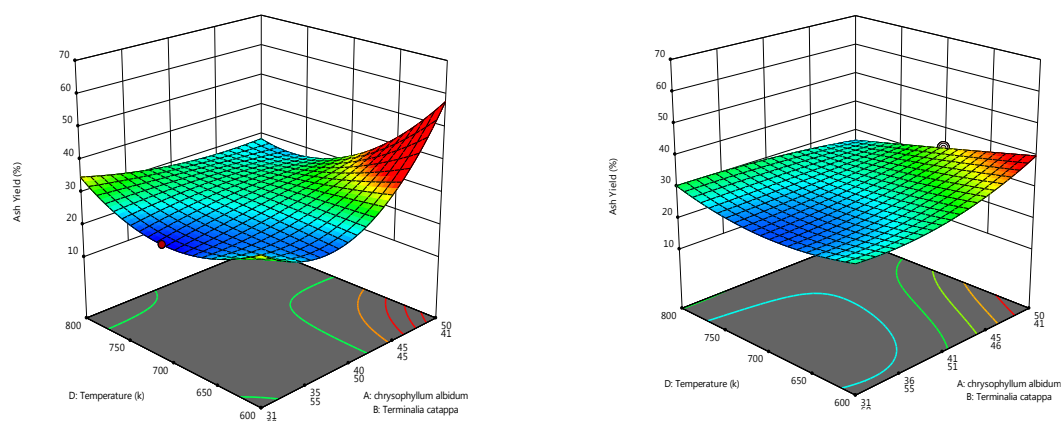
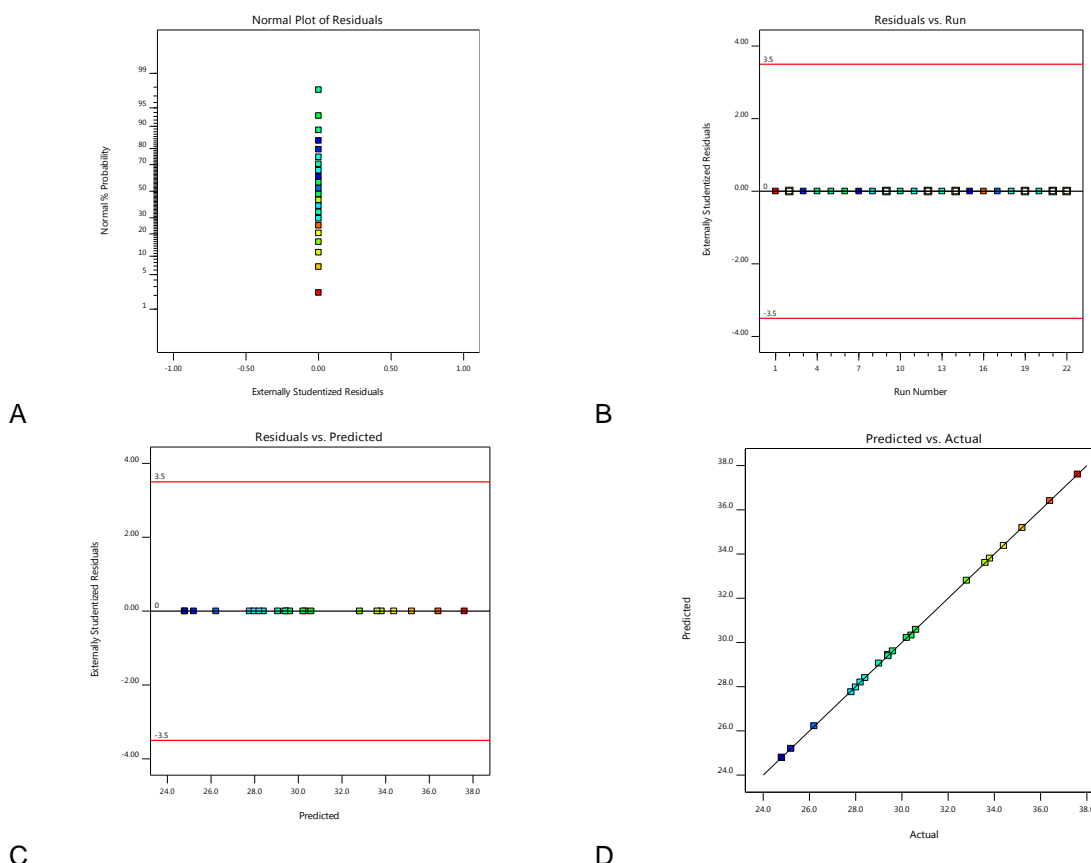


Fig. 2. 3D plots for Ash yield

**Table 3. Statistical analysis of crossed linear models**

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
<b>Model</b>	287.45	20	14.37	872.25	0.0267	significant
Linear Mixture	2.76	2	1.38	83.77	0.0770	significant
AB	3.53	1	3.53	213.98	0.0435	significant
AC	8.39	1	8.39	509.30	0.0282	significant
AD	3.86	1	3.86	234.05	0.0416	significant
BC	13.15	1	13.15	798.00	0.0225	significant
BD	0.0496	1	0.0496	3.01	0.3327	significant
CD	0.0157	1	0.0157	0.9510	0.5080	significant
ABC	2.52	1	2.52	153.10	0.0513	significant
ABD	2.76	1	2.76	167.25	0.0491	significant
ACD	2.46	1	2.46	149.59	0.0519	significant
BCD	0.0306	1	0.0306	1.86	0.4029	significant
AD <sup>2</sup>	6.84	1	6.84	415.10	0.0312	significant
BD <sup>2</sup>	7.44	1	7.44	451.33	0.0299	significant
CD <sup>2</sup>	10.02	1	10.02	608.29	0.0258	significant
ABCD	3.79	1	3.79	230.11	0.0419	significant
ABD <sup>2</sup>	7.78	1	7.78	472.07	0.0293	significant
ACD <sup>2</sup>	9.43	1	9.43	572.56	0.0266	significant
BCD <sup>2</sup>	15.58	1	15.58	945.38	0.0207	significant
ABCD <sup>2</sup>	7.22	1	7.22	437.92	0.0304	significant
<b>Residual</b>	0.0165	1	0.0165			
<b>Cor Total</b>	287.47	21				



**Fig. 3. (a) Normal Plot of Residual, (b) Residuals vs Run, (c) Residuals vs Predicted and (d) Predicted vs. Actual**



### 3.4 Artificial Neural Network

The superiority of artificial neural networks as a modeling tool essentially lies in their ability to represent the non-linearity in bioprocesses efficiently coupled with the capability of learning from historical data [18]. The model performance was examined by using the coefficient of determination or  $R^2$ . The  $R^2$  is a statistical measure that explains the amount of variance between the target values and the predicted results. The  $R^2$  values varied in the range of 0.89 to 0.94 for the ANN model; however, the  $R^2$  values were below the standard for the ANN and

the model varied in the range of 0.26 to 0.99 for the testing subset. The comparison for the performance of artificial neural network models (Fig. 4) shows results of the prediction were compared with different points and scatter plots. A scatter plot is a graph of points that show the relationship between experimental and prediction data. It is a convenient way to present the correlation between two variables. Some of the model predictions deviated from the diagonal line. The Mean Square Error (MSE) indicated that the best validation performance which is 82.9794 occurred at epoch 4 (Fig. 5).

Table 4. Fit statistics

<b>Std. Dev.</b>	<b>0.1284</b>	<b>R<sup>2</sup></b>	<b>0.9999</b>
Mean	30.26	Adjusted R <sup>2</sup>	0.9988
C.V.%	0.4242	Predicted R <sup>2</sup>	-0.3770
		Adeq Precision	102.2429

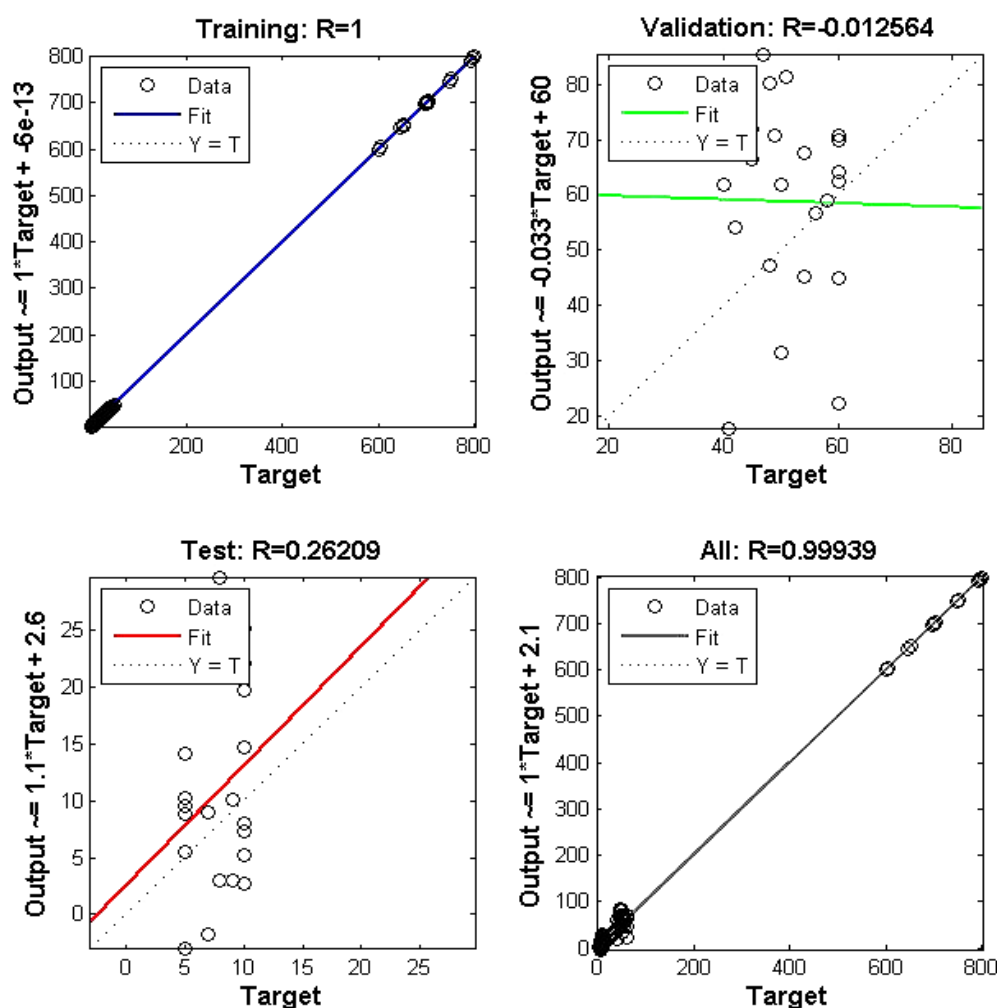


Fig. 4. Artificial neural network

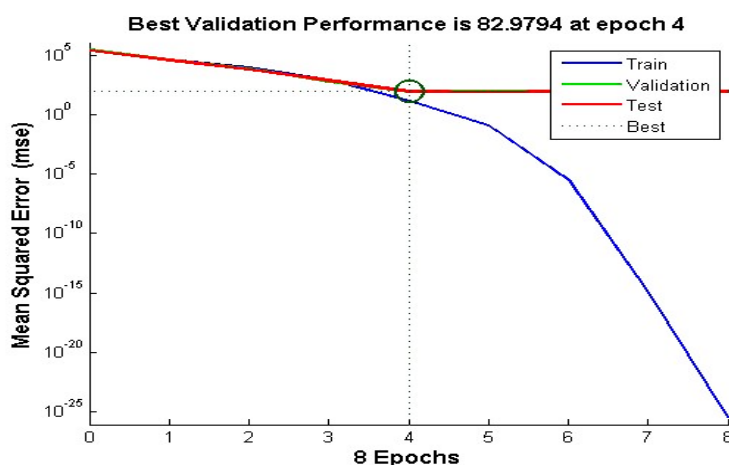


Fig. 5. Plot of optimised iteration

### 3.5 Principal Component Analysis

The principal component analysis produces two items of basic information for interpreting results. The first one is the correlation coefficients between the original variables and the principal components which are used in interpreting the meaning of the principal components. The second one is each principal component is associated with an eigenvalue which converts to the proportion of the variation explained by the principal component. The component loadings are the correlation between the original variables and constructed principal components. This chart graphically displays the absolute values of the component loadings. It lets you quickly interpret the correlation structure. By looking at which variables correlate highly with a component, you can determine what underlying structure it might represent. These plots display scatter plots of the loading values. The points on the plots represent the variables. These plots allow you to see which variables are similar and which are different (Fig. 6). The scatter plots range from -10 to + 11 on the x-axis and -6 to +7 on the y-axis.

### 3.6 Proximate Analysis of Composite Fuel

Proximate analysis of the High and Low African Star Apple shell, Tropical almond and ammonium di-hydrogen phosphate mixture based on the percentage of Ash yield. High Sample shows that the volatile matter, carbon content, moisture content, ash contents, and Higher heating value were 11.00%, 2.34%, 3.20%, 33.80% and 44.87 MJ/kg while Low Sample volatile matter, carbon content, moisture content, ash contents,

and Higher heating value were 7.00%, 2.14%, 6.40%, 24.8% and 30.79MJ/kg (Table 5) shows the proximate analysis of the selected fuel mixtures (Run 19 and Run 7) based on ash yield. The results show that the moisture content, volatile matter, ash contents, and carbon content for Run 19 (38:54:8) were 3.20%, 11.00%, 33.80% and 2.34%, and run 7 (37:56:5) were 6.40%, 7.00%, 24.8% and 2.14% respectively. It was observed that the carbon content and ash content in run 19 (2.34%) was lower compared to run 7 (2.14%) while the volatile matter in run 19 (11.00%) was higher than that of run 7 (7.00%). The lower carbon content is due to the interaction of ammonium di-hydrogen phosphate additives in the fuel mixtures. The moisture content in run 19 (3.20%) was low compared to that of run 7 (6.40%).

The results in Table 6 revealed the fact that the proximate analysis results of samples changed in very wide ranges. That is, the high value of volatile content (11.00%) and the low value of volatile content (7.00%). Compositions of biomass mixture of high are 38% African star apple, 54% Tropical almond, 8% of ammonium di-hydrogen phosphate at 600°C and low is 37% African star apple, 56% Tropical almond, 10% ammonium dihydrogen phosphate at 752°C. On the other hand, the high value of carbon content (2.34%), while the low value of carbon content (2.14%). This confirms that the fuel quality of the high biomass mixture is poor. Besides, the lower limit and the upper limit of carbon content indicate that the high value of carbon content is more than twice the low one. In addition to this, the lowest and the highest values of ash yields were determined as 24.8% and 33.8% for biomass compositions, respectively. In addition

to low carbon content, the high ash yield also confirms the poor fuel quality of biomass material. On the other hand, these yields of ashes also revealed that the most important variations in results took place in the ash yields since some of the biomass species are waste materials that are rich in ash forming inorganics, while woody biomasses do not contain a high amount of inorganics.

The carbon content in this study for both high and low mixture is low compared to previous studies that have higher values, though the ash content for this study has a higher value compared to past studies, this study has 33.80%

for high and 28.4% for a low while [19] got 1.11% and [20,21] got 0.6% respectively. The difference in the results would have been a result of the additive added to this present study. The higher ash content may be beneficial as the ash can be used as a catalyst in thermal conversion technologies [22]. However, varying properties may not be due to the blending and particle sizes only, but a combination of interacting factors such as growing condition, climate, soil, and so on. The high heating value of this study 44.87 MJ/kg and 30.79MJ/kg were obtained for high and low sample mixtures respectively, which is higher than the values obtained for other samples.

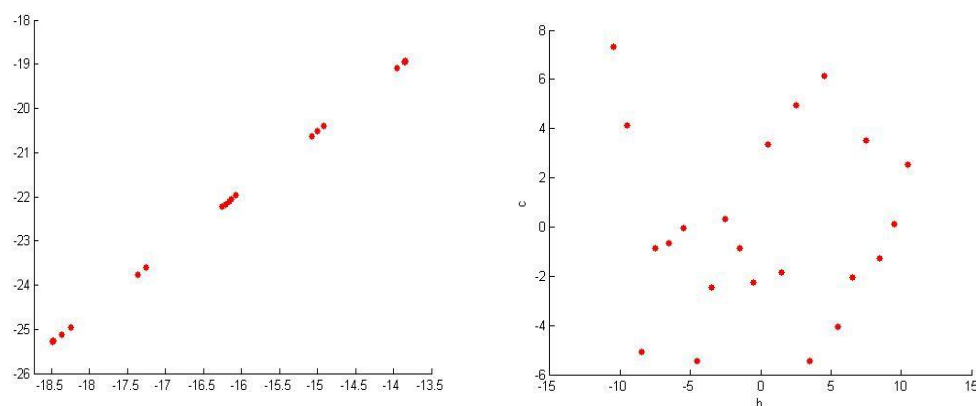


Fig. 6. Principal component analysis model graphs

Table 5. Comparative study for proximate analysis

Sample (mixture)	This Study		Olatunji et al., [19]	Demirbas, [20] [21]
	High	Low		
Volatile content (%)	11.00	7.00	80.93	80.3
Carbon content (%)	2.34	2.14	11.26	15.8
Moisture content (%)	3.20	6.40	6.70	3.3
Heat value (□□/□□)	44.87	30.79	25.07	18.2
Ash (%)	33.80	28.4	1.11	0.6

Table 6. Other tables for comparison

Biomass Materials	Measured HHV (MJ/kg)	Proximate Analysis (%)			References
		Ash	Volatile Content	Carbon Content	
Rice hulls	14.89	20.60	63.60	15.80	[23]
Rice straw	15.09	18.67	65.47	15.86	(Yin, 2011)
Sugarcane	17.33	11.27	73.78	14.95	[23]
Wheat straw	17.51	8.90	71.30	19.80	[23]
Streeter tall wheatgrass	17.90	8.00	73.80	18.20	[23]
Eucalyptus log	17.99	0.37	82.78	8.05	[23]
Almond hulls	18.89	6.13	73.80	20.07	[24]

#### 4. CONCLUSION

[The influence of ammonium di-hydrogen, phosphate additive on ash characteristics of Tropical Almond and African Star Apple upon combustion was investigated in this study. Problematic elements in the ash yield can be controlled and captured optimally with the use of the appropriate additives. Experimentally, the use of the appropriate proportion of ammonium di-hydrogen phosphate additive, tropical almond, and African star apple and particle size has led to reducing ash yield from 37.60 to 24.8%. The optimum conditions of process variables such as tropical almond, African star apple, ammonium di-hydrogen phosphate, and temperature realized were 31%, 60%, 10% 704°C, respectively. Statistical analysis indicates the ash yield from the mixtures of tropical almond, African start apple and ammonium di-hydrogen phosphate additives is best described by the Quadratic model. The  $R^2$  of 0.9999 and the Adjusted  $R^2$  of 0.9988 shows reasonable agreement; i.e., the difference is less than 0.1. A ratio greater than 4 is desirable. The ratio of 102.243 indicates an adequate signal. The model obtained in this work may be utilized in further design works of greater magnitude. The model obtained has potentials for predicting efficient and effective mixture proportions of additives and biomass for the recovery of the least ash content in a furnace. The correlation R for training, validation, testing, and overall performance are 1, 0.26209, -0.012564, 0.99939 respectively using artificial neural network models]

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#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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