



ORIGINAL RESEARCH ARTICLE

RESPONSE SURFACE METHODOLOGY AND ARTIFICIAL NEURAL NETWORK MODELING AND OPTIMIZATION OF LUFFA CYLINDRICA FIBRE PYROLYSIS IN A FIXED-BED PYROLIZER

C. B. Ugwuodo ^{*1}, H. U. Itiri ¹, E. Ogomegbulam ¹, C. Mathew ¹, C. N. Ude ¹,
I. N. Emmanuel ², and S. E Agbokwor ³

¹Department of Chemical Engineering, College of Engineering and Engineering Technology, Michael Okpara University of Agriculture, Umudike

²Department of Chemical Engineering, Nazarbayev University, Astana, Kazakstan

³Department of Mechanical Engineering, University of Nigeria Nsukka

*Corresponding author's email: chijiokeugwuodo@mouau.edu.ng

ARTICLE INFORMATION

Received: 26th February 2025

Revised: 4th April 2025

Accepted: 4th April 2025

Keywords:

Artificial neural networks
Box-Behnken design (BBD)

Bio-oil

Pyrolysis

Response surface
methodology (RSM)

ABSTRACT

Bio-oil production from Luffa fibre, a plentiful agricultural byproduct, has attracted considerable interest as a sustainable and renewable energy source. In this study, response surface methodology (RSM) and artificial neural network (ANN) modelling were used to optimize operating conditions for bio-oil produced by pyrolysis from luffa cylindrica fibre. Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) are used to model and improve operational parameters like temperature, particle size diameter, and inert gas flow rate. This is done to boost bio-oil production and quality. We develop a predictive model for bio-oil characteristics using ANN modelling, which effectively optimizes pyrolysis conditions. This study offers significant knowledge on the production and characteristics of bio-oil derived from luffa cylindrica fibres. By employing both models, we leveraged Response Surface Methodology (RSM) flexibility to provide statistical measures of individual models and their interaction impact on the process output while benefiting from Artificial Neural Networks (ANN) efficiency in processing data and acquiring complex patterns. It offers a method to improve the production process methodically. Comparing the prediction findings of the ANN with those of the RSM, it was shown that the former were superior. Different models have been trained using various transfer functions and varying numbers of neurons with 0.99797, 1.0, and 0.9989 R² values for the training, validation, and test stages, respectively. The proposed network had an overall R² factor of 0.99869. The results were deemed satisfactory based on the overall R² value being near 1.0. The optimization of operational parameters enhances the effective transformation of luffa cylindrica fibre into bio-oil, therefore encouraging the utilization of this sustainable resource for the generation of renewable energy. This strategy aligns with the increasing focus on decreasing the environmental consequences of conventional fossil fuels and promoting alternative and eco-friendly energy supplies.

© 2025 Faculty of Engineering, University of Maiduguri, Nigeria. All rights reserved.

1.0 Introduction

A promising approach in the pursuit of environmentally friendly and renewable energy sources is the conversion of agricultural residues into biofuels (Oasmaa et al., 2016). Biomass pyrolysis is a thermochemical process that decomposes organic materials in the absence of oxygen, resulting in the production of bio-oil, biochar, and gaseous by-products (Sutrisno & Hidayat, 2016). This method is highly effective for converting agricultural residues into renewable energy sources, reducing dependence on fossil fuels while promoting sustainability (Oasmaa et al., 2016). The effectiveness of pyrolysis depends on several operational parameters, including temperature, heating rate, and nitrogen gas flow rate, which significantly influence the quality and

yield of bio-oil (Irfan et al., 2023). Given the rising global demand for sustainable energy solutions, pyrolysis presents a viable approach to addressing energy and environmental challenges (Ryndin et al., 2023).

Among various biomass sources, *Luffa cylindrica*—commonly known as loofah or sponge gourd—has shown significant potential for bio-oil and biochar production through pyrolysis. Its fibrous structure, high cellulose content, and low ash content make it an ideal candidate for energy conversion (Gao et al., 2020). Studies have demonstrated that *Luffa cylindrica* biomass yields bio-oil with a reduced oxygen content and biochar with high carbon concentration, making it a sustainable raw material for bioenergy applications (Fadhil, 2021). Additionally, utilizing *Luffa cylindrica* for bio-oil production helps in waste management by repurposing agricultural residues into valuable energy products (Abbas et al., 2018). The scientific exploration of *Luffa cylindrica* as a biofuel feedstock underscores its relevance in promoting renewable energy and environmental sustainability.

The efficiency of pyrolysis in converting biomass into bio-oil depends on critical factors such as temperature, heating rate, and inert gas flow rate (Anas et al., 2024). Optimal pyrolysis conditions are necessary to maximize bio-oil yield while minimizing undesirable by-products (Wakatuntu et al., 2023). For instance, the study by Abbas et al. (2018) demonstrated that at 500°C, the biochar and bio-oil yields from biomass pyrolysis were 39% and 19%, respectively, highlighting the importance of precise parameter control. Gao et al. (2020) demonstrate that *Luffa cylindrica* fibre possesses favourable attributes for pyrolysis, such as a substantial cellulose content and a minimal ash content. These properties facilitate the production of bio-oil with reduced oxygen level and biochar with elevated carbon content. The study highlights the possibility of *Luffa cylindrica* fibre as a sustainable raw material for pyrolysis, underscoring its adaptability in the applications of bioenergy generation and environmental remediation. Cao et al. (2017) investigated the production of biochar with the aim of creating a highly efficient catalyst for chemical reaction procedures. Gui et al. (2014) assessed the efficiency of fast and slow pyrolyzed bio-oil production methods, specifically examining the control variables of temperature, heating rate, and yield. The study assessed the composition of coconut shells, RHA, and 50% of each component to establish the standards.

Furthermore, Islam et al. (2017) assessed the optimal yield coefficients for bio-oil production using solid waste in a fixed bed reactor set at 500 °C. An examination of the product indicates that the process of pyrolysis of solid waste generates 30% of liquid products and 33% of solid products. As demand for sustainable biofuels grows, optimizing pyrolysis conditions is essential for improving bio-oil quality and ensuring an efficient, scalable process. However, literature is scarce concerning the performance of *luffa cylindrica* fibres for improving characteristics (Bakay et al., 2021).

The utilization of artificial neural networks (ANNs) and Response surface methodology (RSM) has become more prevalent in the optimization of operational parameters for the conversion of biomass to bio-oil (Pazikadin et al., 2020). The methods as mentioned above provide a methodology based on empirical evidence for representing intricate connections between input variables and intended results, hence facilitating faster and more successful optimization procedures (Abbas et al., 2019). Response Surface Method (RSM) is a flexible mathematical technique that provides statistical measures of individual model components and how they interact (Nwosu-Obieogu et al. 2021). The Response Surface Method (RSM) employs a limited quantity of experimental data to construct a precise model for industrial processes. It accurately represents the impact of many input process variables, including both main and interaction impacts, on the process output variable (Nwosu-Obieogu et al. 2022). Artificial Neural Networks (ANN) offer key benefits, especially in applications that need the representation of nonlinear interactions (Kurani et al., 2023). Artificial neural networks (ANN) have the ability to autonomously acquire complex patterns and characteristics from unprocessed input, therefore obviating the necessity for human feature extraction. This capability is particularly advantageous in fields such as picture and speech recognition (Guillod et al., 2020). These methodologies provide data-driven insights, reducing the need for extensive experimental trials while enhancing process efficiency (Abbas et al., 2019). The integration of RSM and ANN in biomass pyrolysis research contributes to the continuous improvement of bioenergy generation systems, making renewable energy production more feasible and sustainable (Waqas et al., 2024). By employing both models, researchers can leverage RSM flexibility to provide statistical measures of individual model and their interaction impact on the process output while benefiting from ANN's efficiency in processing data and acquire complex patterns.

This work aims to use sophisticated methods, namely Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) modelling, to enhance the efficiency of bio-oil production from *luffa cylindrica* fibre by pyrolysis. The objective is to enhance the output and quality of bio-oil by optimizing critical operational parameters such as temperature, inert gas flow rate, and feedstock particle size. This study uses artificial neural network (ANN) modelling to conduct predictive analysis in order to effectively optimize pyrolysis settings.

This analysis yields significant insights into the correlations between process variables and the characteristics of bio-oil. The long-term objective of this work is to methodically enhance the transformation of *luffa* fibre into bio-oil, therefore encouraging the utilization of this sustainable resource for the generation of renewable energy in accordance with objectives related to environmental preservation.

2. Materials and Method

2.1 Preparation of Feedstock

The *luffa cylindrica* fibre used in this study was obtained from a farmland in Amawom village in Ikwuano local government area of Abia state, Nigeria. All foreign materials was removed by washing to ensure the sample is free from impurities. Immediately after the *luffa cylindrica* was sun dried for ten days to remove the moisture content, after which they were ground in a high-speed rotary cutting mill and screened by standard sieve into different particle size diameter according to the design. The nitrogen gas which served as an inert gas was gotten from Aba, in Abia state.

2.1.1 Equipment and chemicals used

Instruments used include, stainless steel reactor, insulator (fibre glass), condenser, Seal (iron gasket), fasteners (bolts and nuts), K-type temperature controller, N₂ gas cylinder, Stop watch, Test Sieves, Weight balance and Electric Heaters.

2.2 Characterization of *luffa cylindrica*

2.2.1 Ultimate analysis of the *luffa cylindrica*

The purpose of this test is to determine element percent of carbon, hydrogen, nitrogen, sulphur and oxygen in the *luffa cylindrica* fibre. The ultimate analysis was conducted according to ASTM standards E777 and E778.

2.3 Experimental Procedures

The pyrolysis of *luffa cylindrica* was carried out in a horizontal lab-scale fixed bed reactor. The stainless steel reactors with a length of 230 mm was used to conduct the experiments. The *luffa cylindrica* sample was fed into the reactor and then closed tightly and initialized with the flow of inert gas (N₂ gas). In each run, a 40 g of the sample biomass was placed inside the reactor and an electric heating elements with a highly sensitive PID (Proportional-Integral-Derivative) controller was used to heat up the reactor to reach the pyrolysis temperature and kept isothermal till desired time (20 min). The temperature inside the reactor was measured by a K type thermocouple. A 6 mm ID and 9 mm OD stainless steel pipe was used to connect the reactor and condenser. The connecting pipe between the reactor and the condenser system was maintained at 200°C to avoid condensation. The condensable liquid products (bio-oil) were collected in a 410 mm length condenser. The temperature of the condenser was maintained at 25°C by circulating the water in the condenser. After each experiment, the condensed liquid was collected into the sample bottle and the liquid weight was calculated by the weight difference of sample bottle before and after the liquid was collected. After pyrolysis, the solid residue was removed and weighed. Then the gaseous phase was calculated from the material balance. The biomass sample input, liquid and solid char were measured by the electro balance weighing machine with an accuracy of +/- 0.01 g. The yield percentage of bio-oil during pyrolysis was estimated using equation below.

$$\% \text{ Yield of Product} = \frac{\text{mass of product}}{\text{mass of feedstock}} \times 100 \quad |$$

2.4 Characterization of Bio-oil

2.4.1 Fourier Transform infra-red (FTIR) Spectroscopy

In this study, functional groups analysis of the bio-oil was carried out using Fourier transform infra-red (FTIR) spectroscopy, Magna-IR550 (Nicolet, Madison). FTIR with an online pen plotter was used to produce the infra-red (IR) spectra of the derived liquids. A small amount of the bio-oil will be mounted on a potassium bromide (KBr) disc. The FTIR spectrum in the ranges of 500-3500cm⁻¹ will be measured and recorded. The absorption frequency spectra is recorded and plotted. The standard IR- spectra of 61 organic compounds will be used to identify the functional group of the components of the derived bio-oil (Rajia et al., 2023).

2.5 Design of Experiment

The RSM was employed based on a Box behnken design in this work for the experimental design. It is a statistical tool often used for fitting quadratic models and is highly reliable when the behaviour of multiple operating parameters on the final results is considered (Hossain *et al.*, 2017). Firstly, the design of the experiment starts with a layout of the design matrix that explains the factors and the response (Savasari *et al.*, 2015). The analysis was performed with bio-oil as the single response in the BBD and temperature, particle size, and inert gas flowrate as the three operating parameters. Each parameter is considered at levels 1, -1, 0, α , and $-\alpha$ (Laouge *et al.*, 2020). The values $-\alpha$ and $+\alpha$ were evaluated using Equation 1, whose value is displayed at -2 and $+2$ where n represents the operating parameters.

$$\alpha = [2^n]^{1/4} \quad 2$$

2.6 ANN Model Development

For ANN, the multi-input-single-output (MISO) architectural neural fitting design in Figure 1 was adopted to model the performance of the process variables and predict the optimal yield of bio-oil. The multi-input variables are temperature, inert gas flow rate, and particle size diameter, while percentage yield of bio-oil produced from *luffa cylindrica* fibre is the single-output. The variables were chosen to investigate the combined influence of input variables on the output variable. The MISO architectural neural network in Figure 1 was design to train 75 % data of the process variables, validate 15 % of the variables, and test 15 % using Levenberg-Marquardt training algorithm. This algorithm takes more memory and less period to run various neurons in the hidden layer. The random data were processed with different number of artificial neurons (10, 12, 15, 19 & 23) in the hidden layer and were trained on the algorithm network. The neuron with the least mean square error (MSE) was taken to be the best performing algorithm network and the interactive effect of the process variable on the output was significant and maximized at data processed with the number of neurons. The best algorithm network was adopted to predict the optimal yield of bio-oil. This was done on a feed-forward back propagation network. The mean square error (MSE) is represented Equation 3. The correlation coefficient (R^2) were determined.

$$MSE = \left(\sum_{i=1}^n \frac{(Predicted\ value - Experimental\ value)^2}{n} \right) \quad 3$$

Where, n = number of datasets used to train the network

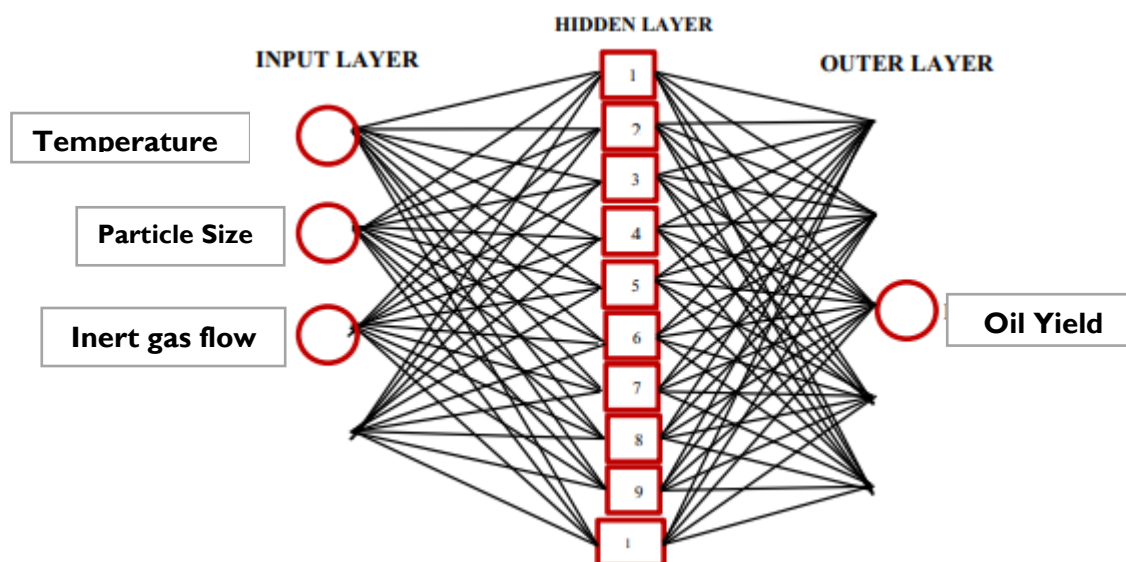


Figure 1: ANN structure

2.7 Optimization of the Experiment

The pyrolysis process was optimized using numerical optimization of design expert as to know the best possible process variables that will maximize the oil yield. The process independent variables (temperature, particle size and inert gas flow) and the response (oil yield) were optimized within the range. The software

provides possible solutions and selects the best as a function of its desirability and importance. A good desirability is close or equal to 1 while a bad desirability is close to or equal to 0.

3. Results and Discussion

3.1 Ultimate Analysis Result

The high carbon and oxygen content indicates that *Luffa cylindrica* is comprised of highly polar structures, which is beneficial to the ion exchange adsorption mechanism. Likewise, the low sulphur, and nitrogen could help limit harmful chemicals deposited in the reactor compartment, consequently, reduce maintenance of the pyrolysis plant. The low sulphur and nitrogen could lead to reducing SO_x and NO_x gases which have adverse effects on the ozone layer in the troposphere (Ayeeni et al., 2018). This compared well with (Anas et al. 2024; Narayan et al. 2021).

Table 1: Ultimate Analysis of *Luffa Cylindrica* Fibre

Elements	Wt %
Carbon	46.5
Hydrogen	6.2
Nitrogen	0.21
Oxygen	37.6
Sulphur	0.91

3.2 FTIR Analysis Result

Fig. 2 depicts the spectra of Fourier Transform Infrared Spectroscopy (FTIR) of bio-oil yields from pyrolysis of *luffa cylindrica* at optimum operating condition over a wavenumber range between 500 and 4000 cm⁻¹ in the spectrum analysis. FT-IR is a chemical analysis technique that detects the different functional groups and chemical bonds in the samples using infrared rays Oyeboji et al. (2022). The FTIR comprises different peaks with strong, medium, and weak intensities corresponding to various bond levels in the bio-oil. The O-H stretching at around 3235.3 cm⁻¹ revealed the presence of alcoholic and phenolic compounds in the bio-oil. The peaks detected at 2922.2 cm⁻¹ and 2855.1 cm⁻¹ with C-H stretching vibrations indicate the presence of alkanes in bio-oil. The strong bond peak at 2079.9 is ascribed N=C=S stretching, indicating Isothiocyanate is present, while the peak 1707.1 cm⁻¹ and 1513.3 are accredited to ester carbonyl (C=O) groups. The medium peak 1379.1 cm⁻¹ and 1401.1 cm⁻¹ are assigned to O-H stretching vibration of the hydroxyl group, carboxylic acid, and water impurities. The vibration between the wavelength 500 and 1200 cm⁻¹ is due to C-F stretching of the fluoro compound. The functional groups' presence is similar to Ogunkanmia et al. (2018) reported. The function group presence in the bio-oil makes it useful as fuel in automobile vehicles, furnaces, and marine equipment. It can also be utilised as a catalyst for the production of drugs and plastic. This results aligns with the report of Sutrisno and Hidayat (2016).

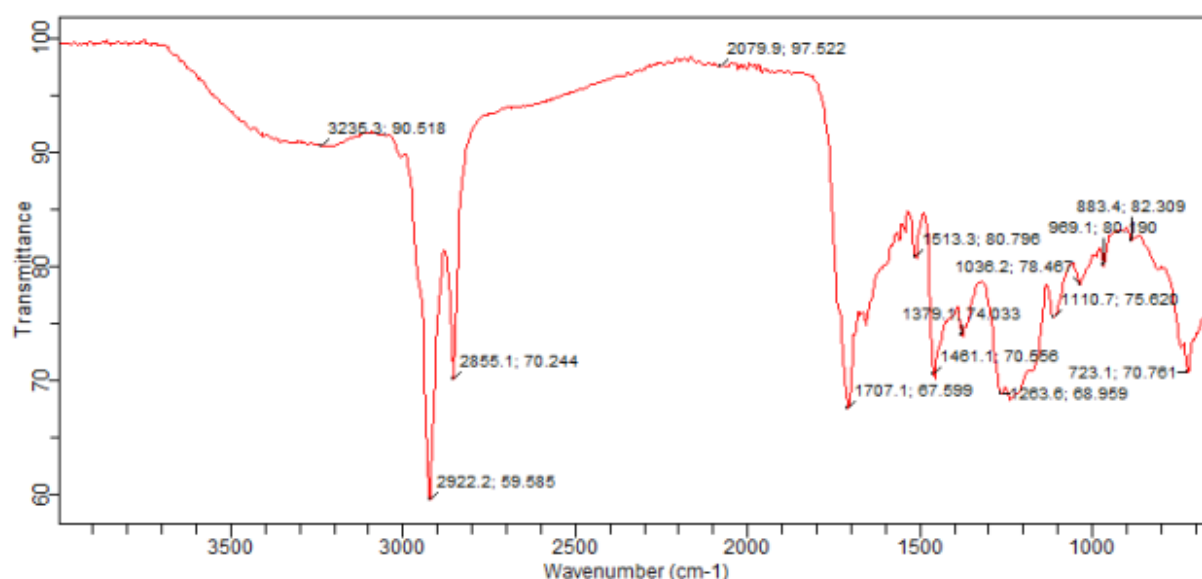


Figure 2: FT-IR spectrum of bio-oil yield from pyrolysis of *luffa cylindrica* fibre

3.3 Response Surface Methodology Modeling for Bio-Oil Yield

The RSM- BBD results for the percentage yield of bio-oil from the pyrolysis process are presented in Table 2. Using design expert software version 13.0.6 USA, three variables, temperature, particle size, and gas flow rate represented by the alphabet A, B, and C, and three levels (-1, 0 and +1) were considered, resulting to seventeen experimental runs. The variation in values of the percentage yield of bio-oil indicated that the process parameters have a significant effect on the pyrolysis process. The maximum percentage yield of 30% occurred at a temperature of 600°C, particle size diameter of 5mm, and inert gas flow rate of 1.5L/min. Second-order polynomial (quadratic) equations in coded terms that defined the independence between the studied process variables (A, B, C) and the response (% yield) for bio-oil were obtained with the use of RSM and represented in equations (Eq.4).

Table 2: BBD experimental design for bio-oil yield

		Factor 1	Factor 2	Factor 3	Response 1
Std	Run	A:Temperature C	B:particle Diameter Mm	C:Inert Gas flow L/min	Oil yield %
17	1	650	5	1	12
11	2	650	4	1.5	7.75
7	3	600	5	1.5	30
16	4	650	5	1	12
12	5	650	6	1.5	22.48
14	6	650	5	1	12
5	7	600	5	0.5	15.5
8	8	700	5	1.5	13.65
15	9	650	5	1	12
2	10	700	4	1	15.2
3	11	600	6	1	21.63
9	12	650	4	0.5	21.25
6	13	700	5	0.5	23.5
4	14	700	6	1	27.6
1	15	600	4	1	25.53
13	16	650	5	1	12
10	17	650	6	0.5	9.55

3.4 Oil Yield Model Statistical Analysis

Analysis of variance (ANOVA) was used to determine the statistical significance of the model and all the regressed coefficients of the developed quadratic RSM-BBD model for the % of bio-oil yield. The ANOVA results for measuring model adequacies for yield of bio-oil are shown in Table 3. The high F – value (62.85), P-value (<0.0001), and non-significant lack of fit (*p-value*> 0.05) indicated that the model was significant (Hidayat *et al.*, 2023).

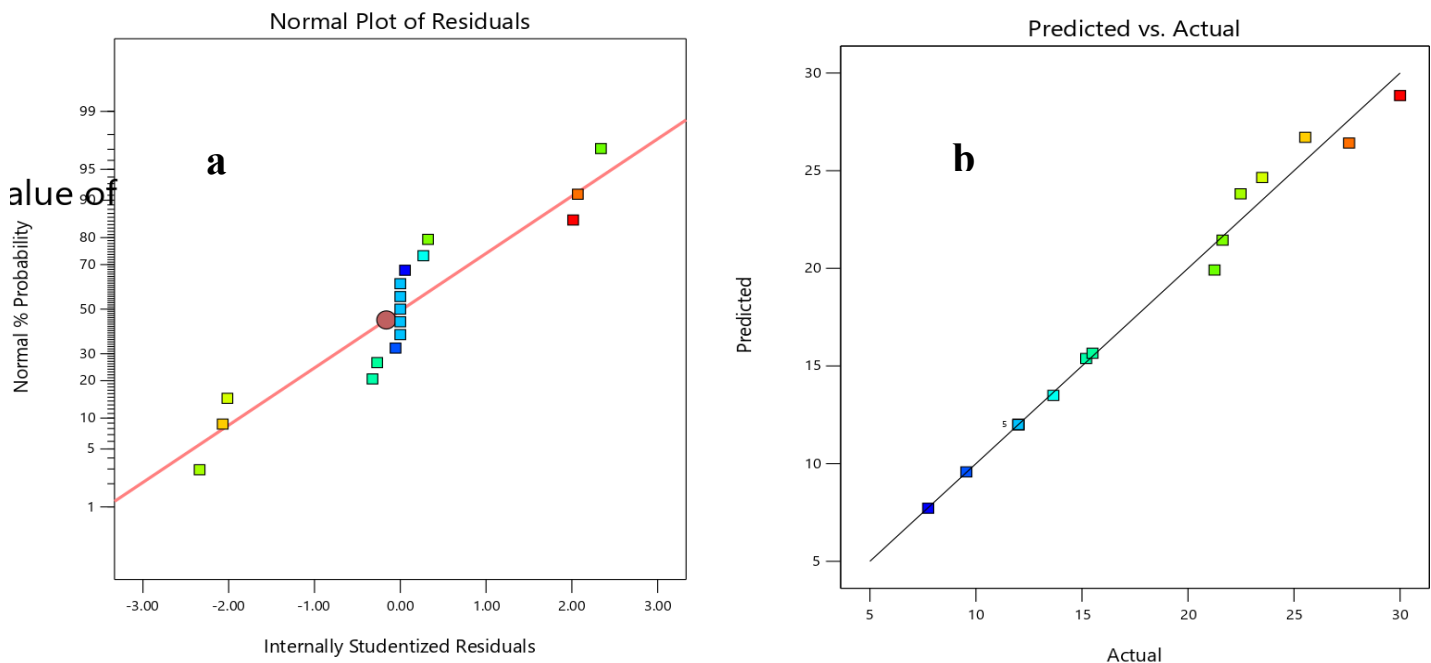
The fitness of the model was expressed by the coefficient of determination (R^2) obtained as 0.9878 with an adjusted R^2 value of 0.9721, which was in reasonable agreement with the predicted R^2 value of 0.8044 for the developed model. This showed that the developed quadratic model had the capability of predicting the observed experimental data within the range of the study (Kamarudin *et al.*, 2019). The adequate precision value of 24.1152, which is a measure of signal-to-noise ratio greater than 4, showed the desirability of the model and indicates an adequate signal. These regression values were in agreement with the report of (Malatji *et al.*, 2020), who suggested that a high correlation confirms the degree of fitness between the predicted and experimental responses. Therefore, this model can be used to navigate the design space.

The linear terms (A, and B), the quadratic terms (A^2 , and B^2) and the interactive effects of temperature: particle diameter: (AB, AC and BC) were all significant ($p < 0.05$) in the oil yield response model. As the process parameters increased, the positive and negative signs in Equation 4 showed an increase and decrease in values of response. Increased A, B, C, AB, AC, and BC led to increased response, while increased values of A^2 , B^2 , and C^2 resulted in decreased response. To check for the normality of the residuals, the normal probability versus studentized residuals plot was considered in Figure 3a. It showed that the points extended well diagonally, suggesting that they were dispersed in a reasonable pattern. The relationship between the predicted and observed actual experimental data in Figure 3b gave a straight line, which showed agreement with each other. Hence the experimental data can be said to be acceptable (Reglioua *et al.*, 2021).

Table 3: ANOVA result for BBD-RSM Bio-oil yield

Source	Sum Squares	of df	Mean Square	F-value	p-value	
Model	738.28	9	82.03	62.85	< 0.0001	significant
A-Temperature	20.19	1	20.19	15.47	0.0057	
B-particle Diameter	16.62	1	16.62	12.73	0.0091	
C-Inert Gas flow	2.08	1	2.08	1.59	0.2472	
AB	66.42	1	66.42	50.89	0.0002	
AC	148.23	1	148.23	113.57	< 0.0001	
BC	174.64	1	174.64	133.80	< 0.0001	
A²	265.95	1	265.95	203.77	< 0.0001	
B²	27.22	1	27.22	20.85	0.0026	
C²	2.15	1	2.15	1.65	0.2399	
Residual	9.14	7	1.31			
Lack of Fit	9.14	3	3.05	1.19	0.471	not significant
Pure Error	0.0000	4	0.0000			
Cor Total	747.41	16				
Std. Dev.	1.14					
Mean	17.27					
C.V. %	6.61					
	R²		0.9878			
	Adjusted R²		0.9721			
	Predicted R²		0.8044			
	Adeq Precision		24.1152			

$$\text{Oil Yield (\%)} = +12 - 1.59A + 1.44B + 0.5100C + 4.07AB - 6.09AC + 6.61BC + 7.95A^2 + 2.54B^2 + 0.7150C^2 \quad (4)$$

**Figure 3:** (a) Normal % probability vs. internal studentized residuals. (b) Predicted vs. Actual values

3.4.1 Parametric analysis on bio-oil yield

In order to gain a better knowledge and understanding of pyrolysis process for oil yield, 3D response surfaces plots were studied. These plots were used to study the interaction effects of the pair of independent variables keeping other variables constant. The 3D response surface plots are the graphical representation of the regression equation used to observe the levels of each factor (Mabrouka et al., 2023). The interactive terms considered are temperature and particle diameter (AB), temperature and inert gas flow (AC), particle diameter and inert gas flow (BC). The interaction between temperature and particle diameter (AB) at fixed inert gas flow on % yield of bio-oil is shown in Figure 4a. The maximum percentage (25.7%) of bio-oil yield was achieved at a temperature of 700°C and particle diameter of 6mm. At temperature levels >650°C, a steady, significant increase in the yield of bio-oil was observed from particle diameter 4 mm to 5 mm, while no significant increase in yield was observed at particle size levels > 5.0 mm. Hence, an increase in AB up to A=700°C and B =6 mm resulted in an increase in % of bio-oil yield. This may be attributed to the fact that

Corresponding author's email address: chijiokeugwuodo@mouau.edu.ng

below the point of 600°C the devolatilization of the feedstock has not started in full force. At this point, depolymerization is still occurring. A similar trend was recorded by Ganapathy and Natarajan (2009).

Figure 4b showed the 3D surface response plot interaction of combined effect of temperature and inert gas flow rate (AC) of bio-oil yield. Increase in AC resulted in increase % yield of bio-oil. This may be a result of adequate devolatilization of the biomass and the ability of the gas to purge the volatile oil into the condenser for condensing to avoid secondary cracking. This corresponds to work done by Álvarez-Chávez *et al.* (2019).

The interaction between particle diameter and inert gas flow rate (BC) was presented in Figure 4c. Increase in BC resulted in significant decrease in % yield of bio-oil. This may be because complete devolatilization of the biomass has occurred and at this point secondary cracking of the biomass only leads to formation of more gases and char, this is similar to the report of (Álvarez-Chávez *et al.*, 2019).

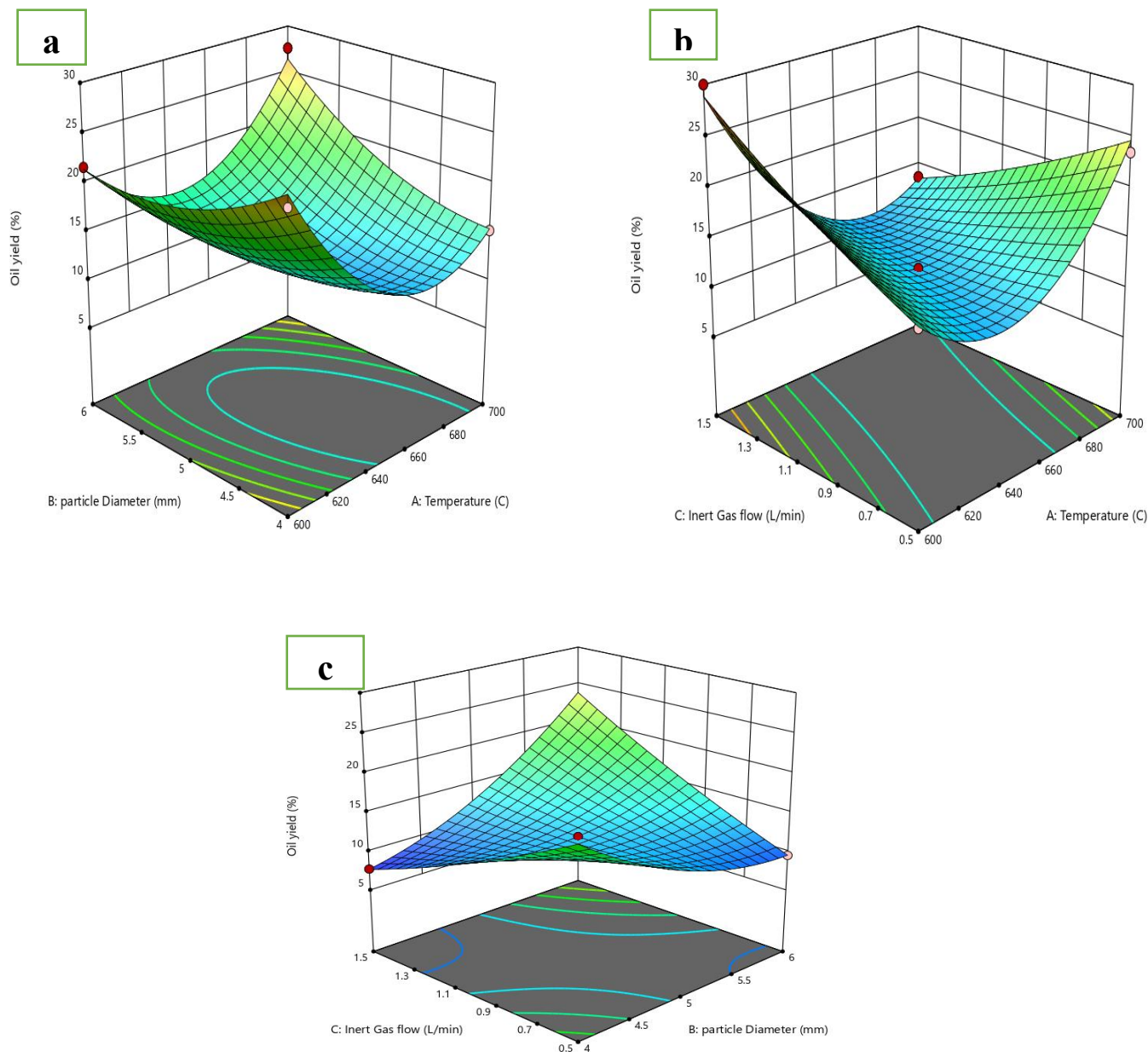


Figure 4: 3D plots on the effect of particle diameter and temperature on bio-oil yield (a), 3D plots on the effect of inert gas flow and temperature on bio-oil yield (b), 3D plots on the effect of inert gas flow and particle diameter on bio-oil yield (c)

3.5 ANN Modelling Results

The ANN-based model was developed based on the multi-input-single-output (MISO) architectural neural fitting design. The optimal model design had 3 neurons in the input layer, 10 in the hidden layer, and 1 in the output layer. Figures 5, 6, and 7 represent the error histogram, plots of regression analysis, and training error

curve performance plot respectively, of the ten activating neurons. Figure 5 shows the MISO network model's error histogram, which shows that the errors were within the range of -0.01802 to 0.04973 (zero region), indicating good performance. Figure 6 shows the best fit between the target data and the output data. The correlation coefficient indicates that the best training, testing, and validation were carried out using the MISO architectural neural network with ten neurons. R-square values indicate extremely high correlation coefficients for the training, validation, and testing sets, ranging from 0.99797 , 1.0 , and 0.9989 , respectively, and the overall R-square was 0.99869 , as shown in Figure 6, suggesting that the model performs exceptionally well and exhibits strong predictive accuracy across different data sets. The values being close to 1 indicate a nearly perfect linear relationship between the predicted and actual values, underscoring the reliability and consistency of the model across various evaluation scenarios. This is in line with the report of Umeagukwu *et al.* (2023) and Anas *et al.* (2024).

At epoch 31, the MSE dropped from 100 to 0.0011666 , as seen in Figure 7. The training and testing of process variables were significantly achieved at epoch 31 at the best performance validation. The maximum number of epochs for performing the best validation was 37. The lower MSE values suggest that the model accurately predicted outcomes. This is in agreement with the report of Anas *et al.* (2024).

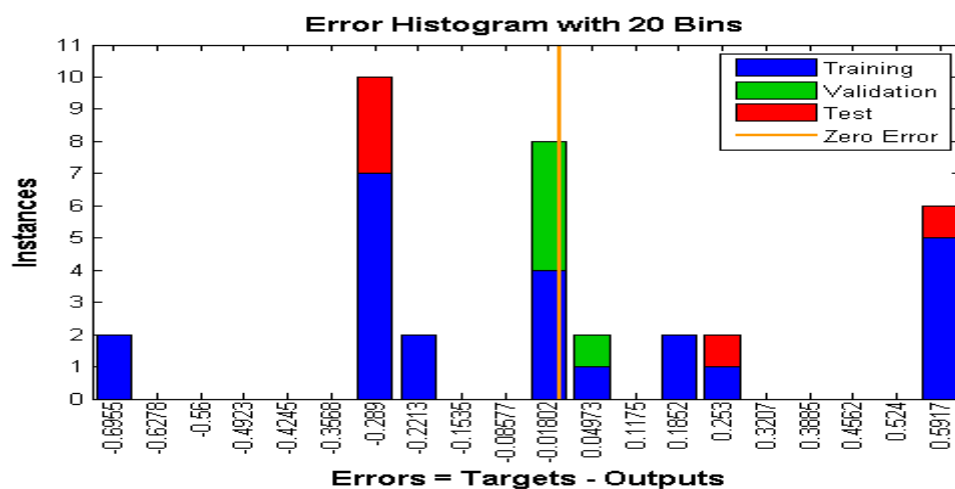


Figure 5: Histogram showing error distribution of experimented data and predicted data on MISO mode

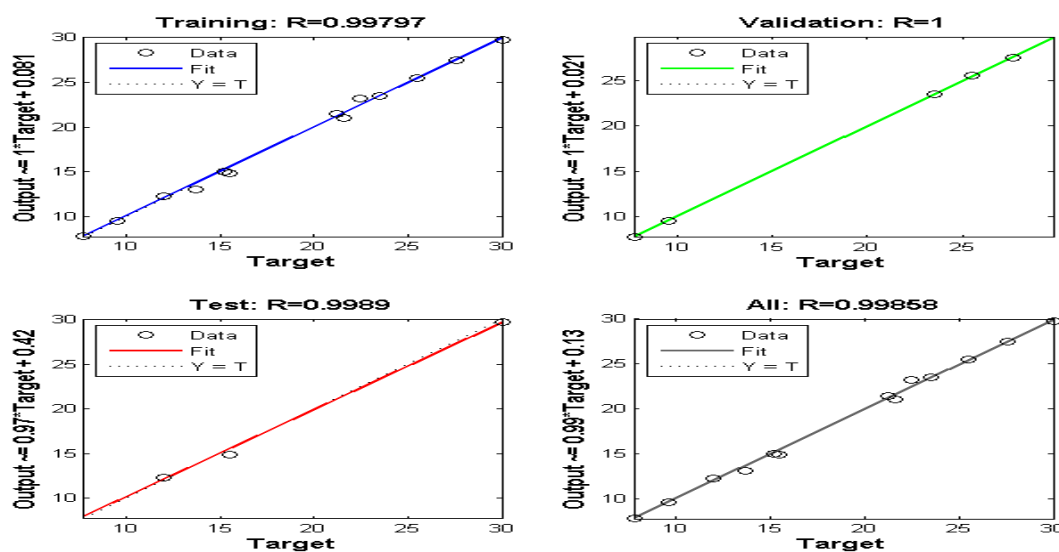


Figure 6: ANN Regression plot analysis for prediction of biodiesel yield using fifteen neurons

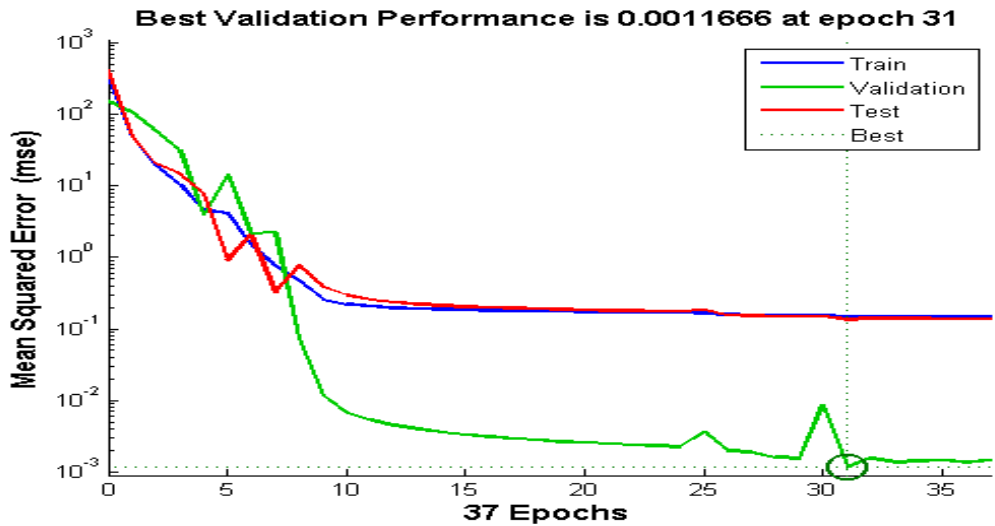


Figure 7: Training error curve for biodiesel yield prediction using fifteen neurons

3.6 Comparing the Predictive Results Output of RSM and ANN

In Table 4, the simulated ANN values from the Levenberg-Marquardt training algorithm alongside the experimental and RSM predicted values for bio-oil yield. The maximum observed oil yield (30%) is in close agreement with RSM (28.85%), and ANN predicted (29.75%); this agrees with the report of Anas *et al.* (2024) in the Optimization of Operational Parameters Using Artificial Neural Network and Support Vector Machine for Bio-oil Extracted from Rice Husk; hence this is an indication that the oil yield from *luffa cylindrica* pyrolysis was affected by the process parameters (temperature, particle size diameter and inert gas flowrate) (Onu *et al.*, 2020).

The predicted results for RSM and ANN were also compared to ascertain the reliability of the models using statistical indicators (R^2 and MSE), as shown in Table 5. It was observed that both coefficients of determination (R^2) of RSM (0.9878) and ANN (0.99797) were close to 1. At the same time, the MSE of RSM (1.14) and ANN (0.0011666) is close to zero, indicating the capability of both models in predicting the pyrolysis process. However, the R^2 of ANN is higher than RSM, and its MSE also lower than RSM, demonstrating that ANN estimated the process better than RSM (Lau *et al.*, 2020; Onu *et al.*, 2020; Betiku *et al.*, 2016).

Table 4: Box-Behnken Design (BBD) predictive RSM/ANN model adequacy

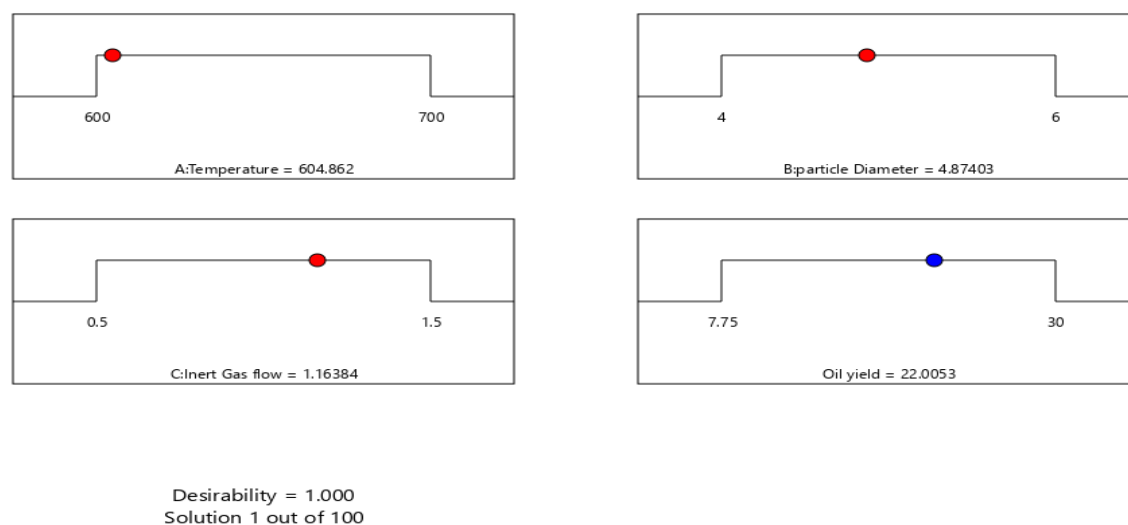
Run	Oil yield (%)	Predicted values	RSM Predicted values	ANN Predicted values
1	12	12	12.27	
2	7.75	7.72	7.75	
3	30	28.85	29.75	
4	12	12	12.27	
5	22.48	23.82	23.21	
6	12	12	12.27	
7	15.5	15.65	14.87	
8	13.65	13.50	13.06	
9	12	12	12.27	
10	15.2	15.39	15.02	
11	21.63	21.45	21.04	
12	21.25	19.91	21.46	
13	23.5	24.65	23.50	
14	27.6	26.42	27.52	
15	25.53	26.71	25.53	
16	12	12	12.27	
17	9.55	9.58	9.55	

Table 5: Comparison of RSM/ANN performance indicators

Performance indicators	RSM	ANN
R^2	0.9878	0.99797
MSE	1.14	0.0011666

3.7 Optimization of the Process

The optimization of the pyrolysis of *luffa cylindrica* fibre was done using the optimization tool of Response Surface Methodology (RSM) and presented in Figure 8. Temperature, particle diameter and inert gas flow were fixed within their experimental ranges of 600-700 °C, 4-6 mm, and 0.5-1.5L/min respectively, and the oil yield were optimized within the range. Optimum operating region for optimization of yield was obtained using the desirability function algorithm of box behnken design. Figure 8 shows values of 604.862°C, 4.87403mm and 1.16384 as the optimum mixture for temperature, particle size and inert gas flow respectively. These values give optimum responses of yield (22.0053%), with desirability of 1.

**Figure 8:** Numerical optimized value of the dependent and independent variables with desirability

4. Conclusions

This work represents a significant advancement in bioenergy production by examining the enhancement of bio-oil production from the pyrolysis of *luffa cylindrica* fibre using approaches such as Response Surface Methodology (RSM) and Artificial Neural Network (ANN) modelling. The predictive capabilities of artificial neural network (ANN) modelling have offered a streamlined method to optimize pyrolysis conditions effectively. The findings of this study provide a meaningful understanding of the complex connections between process parameters and bio-oil characteristics and provide a methodical approach to improving the manufacturing process in line with a broader effort to mitigate the environmental impact of conventional fossil fuels.

References

- Abbas, Q., Liu, G., Yousaf, B., Ali, MU., Ullah, H., Munir, MAM, and Liu, R. 2018. Contrasting effects of operating conditions and biomass particle size on bulk characteristics and surface chemistry of rice husk derived-biochars. *J. Anal. Appl. Pyrolysis*. 134: 281–292.
- Abbas, AK., Al-haideri, NA. and Bashikh, AA. 2019. Implementing artificial neural networks and support vector machines to predict lost circulation. *Egyptian Journal of Petroleum*, 28(4): 339–347.
- Anas, A., Noorfidza, YH., Sharjeel, W., Ushtar, A., and Syed, AG. 2024. Optimization of Operational Parameters Using Artificial Neural Network and Support Vector Machine for Bio-oil Extracted from Rice Husk. *American Chemical Society ACS Omega*. Advance online publication. 6(18): 100424-100438. <https://doi.org/10.1021/acsomega.4c03131>

- Álvarez-Chávez BJ., Godbout S., Le Roux É., Palacios JH. and Raghavan V. 2019. Bio-oil yield and quality enhancement through fast pyrolysis and fractional condensation concepts. *Biofuel Research Journal*, 24(6): 1054-1064. DOI: 10.18331/BRJ2019.6.4.2
- Ayeni, A., Alam, A., Chen, H., Choudhury, IA., Mian, NA. and Islam, MS. 2022. Assessment of different lignocellulosic biomass pyrolysis for bio-oil production: A comprehensive review. *Bioresource Technology*, 34(4): 126188-126205. doi:10.1016/j.biortech.2021.126188
- Bakay, MS. and Ağbulut, U. 2021. Electricity production based forecasting of greenhouse gas emissions in Turkey with deep learning, support vector machine and artificial neural network algorithms. *J. Clean. Prod.*, 28(5): 125324-125349.
- Betiku, E., Odude, VO., Ishola, BN., Ayorinde, B., Osunleke, SA., Okeleye, AA. 2016. Predictive capability evaluation of RSM, ANFIS, and ANN: a case of reduction of high free fatty acid of palm kernel oil via esterification process. *Energy Convers. Manag.*, 12(4): 219–230.
- Cao, X., Sun, S. and Sun, R. 2017. Application of biochar-based catalysts in biomass upgrading: a review. *RSC Adv.*, 7(77): 48793– 48805.
- Fadhil, AB. 2021. Production and characterization of liquid biofuels from locally available nonedible feedstocks. *Asia-Pac. J. Chem. Eng.*, 16(1): 257-279.
- Ganapathy, ES. and Natarajan, E. 2009. Pyrolysis of Coconut Shell: An Experimental Investigation. *The Journal of Engineering Research*, 6(2): 33-39.
- Gao, Y., Yao, Y. and Li, Y. 2020. Pyrolysis of *Luffa cylindrica* fiber for bio-oil and biochar production: Kinetics and product characterization. *Bioresource Technology*, 31(7): 123963-123981. <https://doi.org/10.1016/j.biortech.2020.123963>
- Gui, M. S. Z., Jourabchi, S. A., Ng, H. K., and Gan, S. 2014. Comparison of the yield and properties of bio-oil produced by slow and fast pyrolysis of rice husks and coconut shells. In *Applied Mechanics and Materials*; Trans Tech Publications Ltd, 62(5): 626–629.
- Guillod, T., Papamanolis, P. and Kolar, JW. 2020. Artificial neural network (ANN) based fast and accurate inductor modeling and design. *IEEE Open J. Power Electron*, 20(1): 284–299.
- Hidayat, E., Mohamed Sarbani, NMB, Yonemura, S., Mitoma, Y. and Harada, H. 2023. Application of Box-Behnken Design to Optimize Phosphate Adsorption Condition from water unto novel Adsorption CS-ZL/ZrO/Fe₃O₄: Characterization, Equilibrium, Isotherm, Kinetics and Desorption Studies. *Int. J. Mol. Sci.*, 24(6): 9754-9769. <https://doi.org/10.3390/ijms24119754>.
- Hossain, A., Hasan, MR., and Islam, MR. 2017. Response Surface Methodology for the study of a biomass solid waste pyrolysis system for alternative liquid fuel production. *Global Journal of Researches in Engineering*, 14(5): 1-23.
- Irfan, M., Ghalib, SA., Waqas, S., Khan, JA., Rahman, S., Mursal, SNF. and Ghanim, AAJ. 2023. Response Surface Methodology for the Synthesis and Characterization of Bio-Oil Extracted from Biomass Waste and Upgradation Using the Rice Husk Ash Catalyst. *ACS Omega*. 8(2): 17869–17879.
- Islam, MN., Ali, MHM. and Haziq, M. 2017. Fixed bed pyrolysis of biomass solid waste for bio-oil. *AIP Conf. Proc.* 1875, No. 020015
- Kamarudin, AR., Hamzah, Z., Daud, MZM. and Zakaria, Z. 2019. The Effects of Holding Time and the Sweeping Nitrogen Gas Flowrates on the Pyrolysis of EFB using a Fixed-Bed Reactor. *Procedia Engineering*, 53(7): 185-191.
- Kurani, A., Doshi, P., Vakharia, A. and Shah, MA. 2023. Comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. *Annals of Data Science*, 10(1): 183–208.

Lau, YJ., Karri, RR., Mubarak, MN., Lau, Y.S., Chua, HB., Khalid, M., Jagadish, P. and Abdullah, EC. 2020. Removal of dye using peroxidase-immobilized bucky paper/polyvinyl alcohol membrane in a multi-stage filtration column via RSM and ANFIS. *Environ. Sci. Pollut. Res.*, 27(32): 165-182.

Laouge, R., Agarwal, A. and Kumar, S. 2020. Optimization of extraction processes for bioactive compounds using Design Expert. *Journal of Cleaner Production*, 25(3): 119964-119978.

Malatji, N., Makhado, E. and Ramohlola KE. 2020. Synthesis and characterization of magnetic clay-based carboxymethyl celluloseacrylic acid hydrogel nanocomposite for methylene blue dye removal from aqueous solution. *Environ. Sci Pollut*, 27(4): 44089-44105.

Mabrouka, HC., Sônia, DFR. and Daniel, BR. 2023. Luffa cylindrica Slow Pyrolysis and Solar Pyrolysis: Impact of Temperature and Heating Rate on Biochar Properties and Iodine Adsorption Performance. *Research Square*, 13(17): 9950-9967. DOI: <https://doi.org/10.21203/rs.3.rs-1497697/v1>

Narayan, LP. and Arjun, SP. 2021. An overview of recent development in bio-oil upgrading and separation techniques. *Environ. Eng. Res.*, 26(5): 200382-200398 <https://doi.org/10.4491/eer.2020.382>

Nwosu-Obieogu, K., Oladayo, A., and Goziya, D., 2022. Response surface methodology and artificial neural network modelling and optimization of Colocynthis Vulgaris shrad peel sulphuric acid hydrolysis. *Cleaner and Circular Bioeconomy*, 12(2): 100019-100040.

Nwosu-Obieogu, K., Dzarma, GW., Ugwuodo, CB., Chiemenem, LI. and Akatobi, KN. 2021. Luffa seed oil extraction: Response surface and neuro-fuzzy modelling performance evaluation and optimization. *Process Integration and Optimization for Sustainability*, 5(1): 1–14. <https://doi.org/10.1007/s41660-021-00139-1>

Oasmaa, A., Fonts, I., Pelaez-Samaniego, MR., Garcia-Perez, ME. and Garcia-Perez, M. 2016. Pyrolysis oil multiphase behavior and phase stability: a review. *Energy Fuels*, 30(8): 6179–6200.

Ogunkanmia, FF., James, AO., Olatunde, OO. and Aremu, OJ. 2018. Solid waste management practices and health risks assessment of heavy metals in soils within public healthcare facilities in Abeokuta, Southwest, Nigeria. *The Journal of Solid Waste Technology and Management*, 48(2): 165–173.

Onu, CE., Igbokwe, PK., Nwabanne, JT., Charles, ON. and Ohale, PE. 2020. Evaluation of optimization techniques in predicting optimum moisture content reduction in drying potato slices. *Artif. Intell.n Agriculture*, 16(4): 39–47.

Oyebanji, O., Olatunya, O., Olajide, T., Olajuyin, A., Olajuyin, A., Ogunboyoy, F. and Oluwadiya, K. 2022. Characteristics of the pyrolytic products from the fast pyrolysis of palm kernel cake in a bench-scale fluidized bed reactor. *J. Anal. Appl. Pyrolysis*, 14(5): 104708-104725.

Pazikadin, AR., Rifai, D., Ali, K., Malik, MZ., Abdalla, AN., and Faraj, MA. 2020. Solar irradiance measurement instrumentation and power solar generation forecasting based on Artificial Neural Networks (ANN): A review of five years research trend. *Sci. Total Environ.*, 71(5): 136848-136863.

Rajia, S., Uchhwas, B., Pranab, KN., Muhammad, NH. and Mohammad, I. 2023. Bio-oil production from rubber seed cake via pyrolysis: Process parameter optimization and physicochemical characterization. *Energy Conversion and Management*, 8(20): 100429-100443. <https://doi.org/10.1016/j.ecmx.2023.100429>.

Reglioua, A., Yadav, S. and Kumar, R. 2021. Modeling and optimization of industrial processes using response surface methodology and artificial neural networks: A review. *Computers and ChemicalEngineering*, 14(5):107201-107220. <https://doi.org/10.1016/j.compchemeng.2020.107201>

Ryndin, KG., Butyrin, AV., Grigorenko, AV., Chunzhuk, EA., Chernova, NI., Kiseleva, SV., Malaniy, SY., Bakumenko, EA., Slavkina, OV. and Ossipov, K. 2023. From the Cultivation of Arthrospira platensis at an Increased CO2 Concentration to the Bio-Oil Production by Hydrothermal Liquefaction. *Appl. Sci.*, 13(17): 9950-9972

Savasari, SV., Aondoakaa, EM., Suleiman, MM., Olayemi, JK. and Gana, AS. 2015. Experimental investigation of energy generation from *Luffa cylindrica* plant as a renewable energy source. *International Journal of Energy and Environmental Engineering*, 12(3): 335-344. doi:10.1007/s40095-021-00413-6

Sutrisno, B. and Hidayat, A. 2016. Upgrading of bio-oil from the pyrolysis of biomass over the rice husk ash catalysts. IOP Conf. Ser.: Mater. Sci. Eng., 162, No. 012014

Umeagukwu, OE., Dominic, OO. and Callistus, NU. 2023. Methanolysis of African pear seed oil catalyzed with acid activated empty palm fruit bunch ash: Optimization and sensitivity analysis. *Cleaner Energy Systems*, 6(2): 100093-100106

Wakatuntu, J., Olupot, PW., Jjagwe, J., Menya, E. and Okure, M. 2023. Optimization of pyrolysis conditions for production of rice huskbased bio-oil as an energy carrier. *Results in Engineering*, 17(8): 100947-100962.

Waqas, S., Harun, NY., Arshad, U., Laziz, AM., Mun, SLS., Bilad, MR., Nordin, NAH., and Alsaadi, AS. 2024. Optimization of operational parameters using RSM, ANN, and SVM in membrane integrated with rotating biological contactor. *Chemosphere*, 34(9): 140830-140847.