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Research Article

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Special Issue

A Themed Issue in Honour of Professor Onukwuli Okechukwu Dominic (FAS).

This special issue is dedicated to Professor Onukwuli Okechukwu Dominic (FAS), marking his retirement and celebrating a remarkable career. His legacy of exemplary scholarship, mentorship, and commitment to advancing knowledge is commemorated in this collection of works.

Edited by
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Multi input multi output optimisation of waste cooking oil methanolysis for conventional biodiesel production

Ogbodo, Nkiruka Jacinta[1*], Esonye, Chizoo[1], Onukwuli Okechukwu Dominic[2] and Okahu Alpheus Chijindu[1]

[1]Alex Ekwueme Federal University Ndufu Alike Ikwo, Ebonyi State, Nigeria.
[2]Nnamdi Azikiwe University, Awka, Anambra State.
Corresponding author's email: nkirukaogbodo@yahoo.com

Abstract

This research studied the optimization of biodiesel production from conventional sodium hydroxide (NaOH) homogenous catalyst and waste cooking oil (WCO) using central composite design-based response surface methodology (CCD-RSM), compared with artificial neural network (ANN). The input parameters (methanol: oil ratio, catalyst dosage, agitation rate, reaction time and temperature) were studied for their comparative impact on biodiesel output parameters (yield, viscosity, flashpoint, cetane number and cloud point). The optimization process produced optimized values of 87.47 % and 89.40% respectively for the experimental yield of 90% for the CCD-RSM and ANN respectively at the optimal conditions of methanol-to-oil molar ratio of 6:1, catalyst concentration of 0.5 wt%, agitation rate of 300 rpm, reaction time of 50 min at 50 °C reaction temperature. The corresponding multi responses for the flash point was 144 °C, Viscosity (6.92 mm^2/s), cetane number (42.0) and cloud point (5 °C). The reliability result using the coefficient of determination (R^2) confirmed the CCD-RSM and ANN validation as 96.90% and 99.90% respectively showing that the models predicted the values properly with ANN giving a better result. This proves that ANN machine learning isa better technique for the optimization of the homogenously catalyzed biodiesel production yield from waste cooking oil. The quality of the produced biodiesel was confirmed using ASTM D 6751 standard method of analysis.

Keywords: Multi input, multi output, optimization, waste cooking oil, methanolysis, conventional biodiesel

1. Introduction

To reduce dependence on the use of fossil fuel due to the highly negative environmental implication of the process has necessitated an increased concern for research for more sustainable, environmentally friendly and renewable fuels such as biofuels (Cunha et al., 2022 and Onukwuli et al., 2020). Biofuels, basically comprising of biodiesel, bioethanol and biogas are gaining more attention as viable options for future energy fuels. Biodiesel is a mixture of fatty acids that is biodegradable, renewable, and nontoxic fuel (Mansir et al. 2018), conventionally synthesized from plant-based vegetable oil and animal fat feedstock through transesterification process (Attari et al., 2022) as shown in Figure 1. Different edible oils and non-edible seed oils used in recent past for the transesterification biodiesel includes soybean oil, rapeseed oil, and palm oil (Colombo et al., 2019 and Essamlali et al., 2019) and Jatropha curcas, Ricinus communis, Madhuca indica, and Pongamia pinnata oils (Awais et al., 2020; Kaur and Bhaskar, 2020, Arumugam and Ponnusami, 2019, Elango et al., 2019). Presently, the production of biodiesel processes is mostly at the laboratory stage and is relatively costly to commercialize due to the cost of the feedstock and the minimal efficiency of the process. However, in recet times, waste cooking oil is considered as a favourable feedstock for the biodiesel synthesis due to its low cost compared to edible and non-edible oils (Mardhiah et al., 2017).

Besides feedstocks, the use of catalyst (homogenous or heterogenous) in biodiesel production reduces the activation energy of the process by increasing the solubility of alcohols in the oils, thereby speeding up the procedure for more efficient conversion to obtain desired product. The transesterification method of biodiesel production is strongly dependent on the use of catalysts and the choice of catalyst is very crucial for the biodiesel yield and the quality of the product. The most commonly used homogeneous catalysts for the production of biodiesel are NaOH and KOH (Gupta and Rathod, 2018).

Experimental design for enhancing the response parameters of a production process to reduce cost by manipulating the input parameters is considered expensive, monotonous and time-consuming task but a very crucial step for the optimization of the processes (Jana et al., 2022). However, to arrest the instability of renewable energy production processes is currently the direction of many researchers (Esonye, et al., 2023). For the biodiesel production systems, several factors can influence the response parameters such as methanol: oil ratio, reaction temperature and duration catalysts dosage and agitation rate. Response surface methodology (RSM) has been documented as a reliable optimization technique in various research and industrial processes that could reduce the number of experimental steps needed to produce substantial results (Elkelawy et al., 2020). RSM is generally used to forecast and optimize the response parameters and input parameters respectively. Artificial Neural Networks (ANN) is a biologically inspired computational technique that imitates the behavior and learning process of the human brain for simulations of the behaviour of biological neurons, data classification, modelling of non-linear functions, clustering and non-parametric regression using network training methodology to predict target values with considerably higher accuracy levels (Maleki et al., 2023). The networks are applied in many fields to model and predict the behavior of unknown systems based on investigation of given input-output data. Consequently, RSM and ANN are among the machine learning tools that is considered as traditionally advanced and effective tools for the optimization of industrial processes in the recent past with substantial advancement in purpose driven algorithms to handle various data distribution (Zhang et al.,2020).

In recent past, several researchers have worked on the optimization of biodiesel process to improve the effectiveness of the production steps. Foroutan et al., (2021), studied the influence of input process variables in biodiesel production optimization to determine biodiesel yield by RSM and ANN tools. They observed that biodiesel output gave 98.76% and 97.75% respectively for the RSM and ANN tools with RSM performing better than ANN model. Ayoola et al., (2020), extensively researched on the optimization of biodiesel production from crude palm kernel oil using the two models confirming a better performance of the RSM model for predicting biodiesel yield. Other prominent examples include the optimization of biodiesel production and optimization using sunflower oil, soybean oil and neem oil using RSM and ANN tools ((Elkelawy et al., 2020).

Currently, most researchers focus on the optimization biodiesel production from different feedstock by manipulating the input parameters to majorly determine the output yield using different machine tools, however, scarce report have been observed on the multi-input multi output optimization of the process, hence, this present study aims to optimize the multiple input parameters and multiple output responses for transesterification of waste cooking oil catalyzed by sodium hydroxide (NaOH) using CCD-RSM and ANN machine learning tools. The effect of the independent variables, Catalyst dosage, methanol: oil ratio (M:O), reaction temperature, reaction time and agitation rate on the WCOME yield with the corresponding flash point, viscosity, cetane number and cloud point properties at the optimal conditions were investigated. The accuracy of each model and the comparative analysis is also done based on the statistical analysis to determine the coefficient of determinant (R^2) values of the developed models.

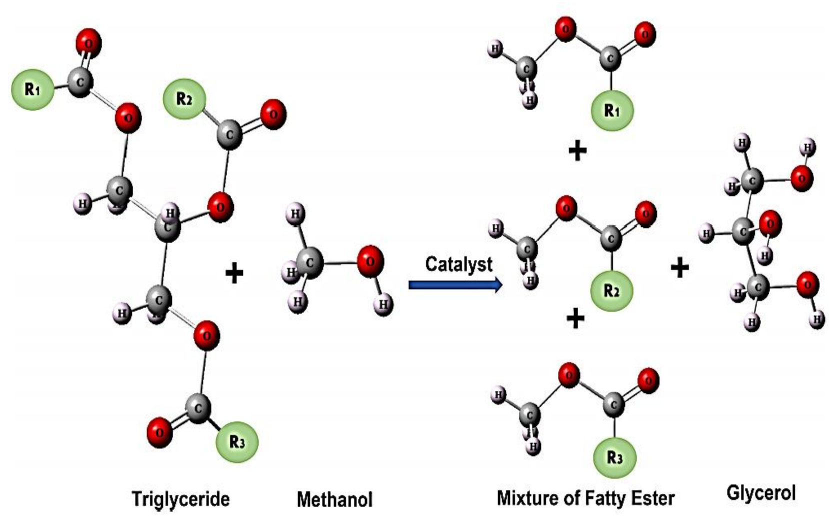

Figure 1: Pictorial view of transesterification reaction model.

2. Materials and Methods

Waste cooking oil was collected from the cafeteria in Ndufu Alike of Ikwo Local government in Ebonyi state. The reagents were obtained from a local market in Engu, Engu state. All the reagents were of Analytical grades and used without further treatment. The apparatus used for the transesterification process includes; three-arm round bottom flask, volumetric flask, separating funnel, hot plate magnetic stirrer, thermometer, flask holding stands and condenser attached to the conical flask.

2.1 Waste cooking oil (WCO) Pretreatment process

Firstly, the WCO was filtered using Whatman filter paper to eliminate any solid particles suspended in the oil, followed by multiple times hot water washing. The waste cooking oil is heated in a microwave oven at a temperature of approximately 105 ◦C for 3-5 mins to effectively eliminate any water content present and the acid value and FFA of the waste oil were determined by titration process using the equations (1) and (2), Normally the free fatty acid value of the waste cooking oil sample needs to be below 2% for optimum conversion to biodiesel, the process of washing and filtering reduced the FFA value of the WCO hence one step transesterification process was used for the biodiesel production.

$$\text{Acid Value (AV)} = \frac{(56.1\, x\, V x\, N)}{W} \tag{1}$$

$$\text{FFA} = 2\text{AV} \tag{2}$$

2.2 One Step Transesterification of pretreated WCO

100ml of waste cooking oil was heated and washed with hot water to remove the impurities and organic contaminants in the oil. 50ml of the pretreated waste cooking oil was used for the process using methanol as the reagent and sodium hydroxide (NaOH) as the homogenous catalyst adopting the method by Esonye, et al., (2020) with slight modifications. For the transesterification process, the WCO sample was firstly heated up to 70 ^{o}C temperature before introducing a specific mixture of NaOH catalyst and methanol based on the experimental design of the process as shown in Table 1. The mixture was stirred at the specified agitation rate and the temperature was maintained at a specific temperature for a specific reaction time as also stated in the experimental design Table 1. At the end of each reaction time, the resulting products was transferred to separating flask for settling and separation of the waste product (glycerin) and the main product (biodiesel). Finally, the product was heated at a temperature of 105 ◦C for 5 minutes to remove any moisture content. The physicochemical characterization of waste cooking oil and the produced biodiesel from this process were carried using American standard Testing Method (ASTM) and the values obtained presented in Table 2 while Figure 2, shows the steps involved this transesterification process.

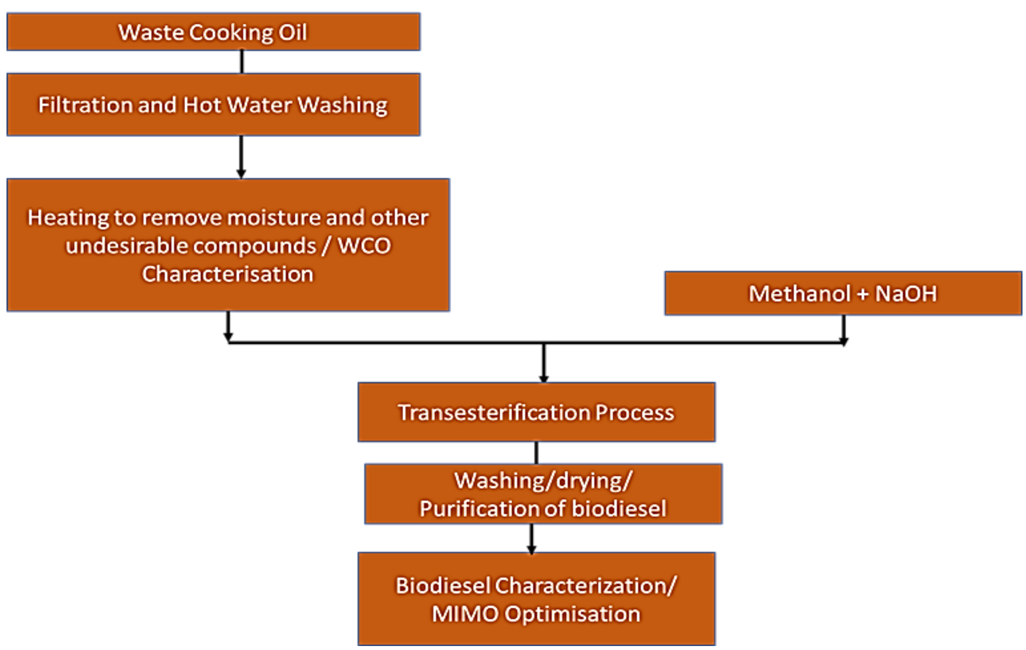

Figure 2: Biodiesel production and Optimization steps.

2.3 Experimental Design

Central composite design-based response surface methodology (RSM) tool was employed as a statistical modelling tool to design the reaction matrix based on the experimental design Table 1., to determine the optimum values of reaction parameters from the experimental responses. For this study, five factor five level variables and quadratic polynomial equations were applied to create the connection between the reaction input parameters (methanol to oil ratio, catalyst dosage, reaction time, reaction temperature and agitation rate) leading to a total of fifty experimental runs, and the response parameters (yield, flash point, viscosity, cetane number and cloud point).

Table 1: Factors and their levels of CCD for homogenous process

Factor	Units	Symbol	Coded Levels				
			-α	**-1**	**0**	**+1**	**+α**
Catalyst Dosage	w%	A	0.5	0.75	1.0	1.25	1.5
Reaction Temperature	ºC	B	40	50	60	70	80
Reaction Time	Mins	C	50	60	70	80	90
Methanol/Oil Ratio	Mol/mol	D	3:1	6:1	9:1	12:1	15:1
Agitation	rpm	E	100	150	200	250	300

2.4 Statistical Analysis Using RSM

To optimize the biodiesel outputs, various experimental steps (50 runs) were obtained using CCD based response surface methodology. To fit the experimental data obtained from the experimental runs, a quadratic polynomial model was designed and equations (3-7) represent the model equations for the process responses. The statistical data from the analysis of variance (ANOVA) are also included below each equation.

Oil yield (%) = +78.21-7.70A + 0.21B -003C +0.62D + 1.36E +1.69AB -0.44AC -0.063AD -1.44AE + 0.69 BC - 1.19BD - 0.31BE -1.31CD + 2.06CE -3.81DE - 1.40A^2 - 2.11B^2 - 0.17C^2 + 0.72D^2 - 0.8E^2 (3)

R^2 = 0.9690 **Adjusted R^2 =** 0.9477 **Pred R^2 =** 0.9129 **Adequate Precision =** 7.876 **C.V % =** 10.45

Viscosity (m²sec) = +7.12 - 5.56A + 0.75B + 0.61C - 5.59D - 0.060E - 0.35AB 0.97AC + 2.05AD + 0.47AE + 1.07BC - 0.83BD + 0.34BE - 0.37CD - 0.30CE +0.75DE + 4.85A^2 + 0.41B^2 + 0.58C^2 + 1.10D^2 + 0.79E^2 (4)

R^2 = 0.9816 **Adjusted R^2 =** 0.9690 **Pred R^2 =** 0.9216 **Adequate Precision =** 12.743 **C.V % =** 41.86

Flash point (°C) = +134.30 - 6.95A + 1.54B + 0.064C - 6.28D - 1.91E - 2.19AB - 1.94AC + 0.81AD -0.56AE -1.31BC - 1.81BD + 1.19BE + 1.19CD + 2.81CE+ 0.81DE + 3.11A^2 + 1.69B^2 + 2.75C^2 + 0.81D^2 + 2.05E^2 (5)

R^2 = 0.92039 **Adjusted R^2 =** 0.90686 **Pred R^2 =** 0.87549 **Adequate Precision =**10.307 **C.V % =** 4.91

Cetane Number = +53.75 + 2.48A - 0.88B - 0.76C + 3.78D - 1.01E + 0.61AB + 0.59AC - 0.90AD - 0.80AE-0.63BC - 1.30BD - 0.68BE - 0.20CD + 0.083CE - 1.11DE - 2.86A^2 + 0.36B^2 - 0.87C^2 - 1.74D^2 - 1.28E^2 (6)

R^2 = 0.9005 **Adjusted R^2 =**0.8864 **Pred R^2 =** 0.8487 **Adequate Precision =** 7.084 **C.V % =** 11.83

Cloud point (°C)= +2.18 - 0.78A + 0.18B + 0.053C - 0.98D + 0.043E - 0.047AB 0.20AC + 0.14AD + 0.11AE + 0.14BC - 0.078BD + 0.016BE + 0.016CD 0.078CE + 0.078DE + 0.66A^2 + 0.13B^2 + 0.13C^2 + 0.18D^2 + 0.27E^2 (7)

R^2 = 0.9718 **Adjusted R^2 =** 0.9622 **Pred R^2 =** 0.9292 **Adequate Precision =** 10.863 **C.V % =** 29.23

3. Results and Discussion

This section of the research involves the investigation of the NaOH alkali based homogenous catalytic process for biodiesel production. The fuel characteristics of the waste cooking oil and the produced biodiesel from WCO were obtained through ASTM D6751 and AOAC standard methods. Afterwards, the optimization and statistical analysis were carried out employing RSM and ANN modelling tools. The accuracy of the models was thoroughly assessed based on the determinant coefficient (R^2) of the statistical analytical tools.

3.1 Physiochemical Properties of raw WCO and WCO Biodiesel

The fuel properties of the waste cooking oil produced biodiesel were studied at optimal condition following international ASTM standards. The waste cooking oil biodiesel properties were compared with the international standards as shown in Table 2. According to Table 2, calculated value of the fuel density, flash point, kinematic viscosity, flash point, cloud point and cetane number correspond to the ASTM D6751 international standard which indicates its suitability to be used in diesel engine.

Table 2: Physiochemical properties of WCO and WCOME

Properties	WCO	WCOME	ASTM D6751	EN 14214
Moisture Content (%)	1.049	0.025	< 0.03	0.02
Density (g/ml)	0.987	0.878	0.86–0.90	0.85
Viscosity at 40°C (mm^2/s)	43.40	5.68	1.9–6.0	3 .5–5.0
Flash point (°C)	246	168	130min	120min
Acid value (mgKOH/g)	12.11	0.232	0.5 max	-
Free fatty acid (%)	6.06	0.116	0.5 max	-
Pour point	-	5.2	-15 – 10	-
Saponification value (mgKOH/g)	208	175	-	-
Iodine value mg/100g	73.58	92.26	48 – 60	-
Cetane Number	-	56	47 min	51 min
Heating Calorific Value (KJ/mol)	39.20	45.34	36 min	-
Cloud point	14	6.5	-3 - 12	-

3.2 WCOME fatty acid composition Analysis

Table 3 shows the WCOME fatty acid composition profile obtained by using GCMS equipment. According to result in Table 3, the main fatty acids in the waste cooking oil were oleic acid (C18:1), linoleic acid/Octadecadienoic acid (C18:2 and C18:3) and palmitic acid/ Hexadecanoic (C16:0) with the mass composition of 16.09%, 44.41% and 9.7% respectively for HWCOME and oleic acid (C18:1), linoleic acid/Octadecadienoic acid (C18:2 and C18:3) and palmitic acid/ Hexadecanoic (C16:0) with the mass composition of 17.4%, 59.18% and 19.64% respectively. The unsaturated fatty acids level of 54.11% present in WCOME is higher compared to the level of saturated fatty acids (16.09%). The higher quantity of unsaturated fatty acid, however indicates a better cold flow property of the WCOME.

Table 3: Fatty acid composition of homogenous waste cooking oil methyl ester (WCOME)

S/n	Library/ID	Retention Time	Percent Composition
1	9,12-Octadecadienoic acid	5.4904	2.5087
2	2-Hexadecanoic	9.6986	0.1125
3	9,12-Octadecadienal	20.0696	0.5708
4	6,11-Dimethyl-2,6,10-dodecatrien-1-ol	29.6504	6.2364
5	13-Oxabicyclo[10.1.0]tridecane	31.4498	4.7592
6	9,12, 15-Octadecatrienoic	32.167	9.8029
7	9,12-Octadecadienoic acid	32.7919	7.7694
8	Oleic Acid	33.1884	6.6709
9	9-Oxabicyclo[6.1.0]nonane	33.8934	8.7466
10	9,12-Octadecadienoic acid	34.0393	4.3073
11	9,12-Octadecadienoyl chloride	34.6161	7.7609
12	Oleic Acid	34.7702	4.1611
13	9-Oxabicyclo[6.1.0]nonane	35.4895	6.2966
14	Oleic Acid	35.9129	5.2555
15	9,12-Octadecadienoic acid	36.6324	11.6896
16	9-Oxabicyclo[6.1.0] nonane	37.1739	4.3652
17	Cyclotetracosane,	37.9916	8.9864

3.3. Process Parameters Optimization Using RSM

Composite central design (CCD) based response surface methodology (RSM) was implemented to find the correlation between WCOME yield, viscosity, flash point, cetane number and clod point with process parameters selected for the response parameters optimization study. Table 4 presents the statistical outcomes of the process, which shows that the model is significant. This conclusion is also supported by the positive F value of 3.24 and the small p-value of 0.002 for the model. The p-value is employed to assess the significance of each process parameter by revealing the significance of the combined effect of process parameters on biodiesel yield. Consequently, from Table 4, the process variables catalyst dosage (A), reaction temperature (B) and agitation rate (E) are the main parameters that substantially influences the WCO biodiesel production using homogenous catalyst. Among these variables, the catalyst dosage(A) impacts the conversion efficiency of WCO to WCOME significantly as a result of the high F value of 41.9 and its lower p-value (<0.0001) when compared with other analyzed process parameters. Figure 3 demonstrates the correlation between the experimental data and predicted data from the empirical model for the biodiesel yield. The correlation coefficient (R^2) and the Adjusted R^2 obtained were 0.9690 and 0.9477 respectively. The minor difference of 0.0213 obtained between R^2 and Adjusted R^2 denotes the significance and usefulness of all reaction parameters involved.

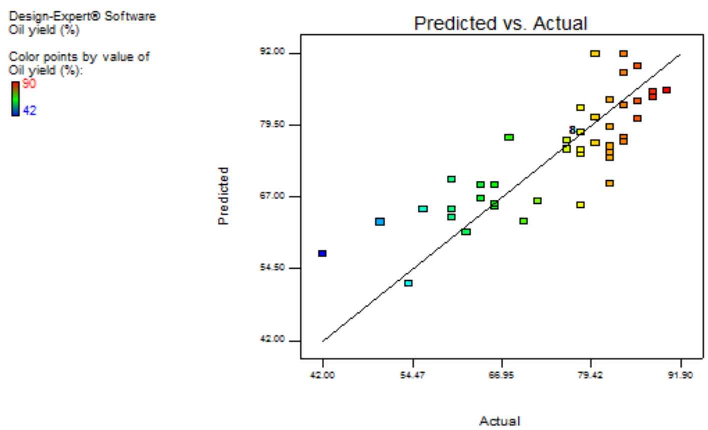

Figure 3: Plot of predicted values versus experimental values for the WCO biodiesel yield.

Table 4: ANOVA for response surface quadratic model for WCO biodiesel yield

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	3961.67	20	198.08	3.24	0.002	significant
A-Cat dosage (wt%)	2565.56	1	2565.56	41.9	< 0.0001	
B-Rxn Temp (°C)	1.97	1	1.97	0.032	< 0.0001	
C-Rxn Time (min)	6.89E-05	1	6.89E-05	1.13E-06	0.9992	
D-Methanol/oil ratio (mol/mol)	16.53	1	16.53	0.27	0.6073	
E-Agitation rate (rpm)	80.59	1	80.59	1.32	< 0.0001	
AB	91.12	1	91.12	1.49	0.00323	
AC	6.13	1	6.13	0.1	0.7541	
AD	0.13	1	0.13	2.04E-03	0.00643	
AE	66.12	1	66.12	1.08	< 0.0001	
BC	15.12	1	15.12	0.25	0.6229	
BD	45.12	1	45.12	0.74	0.3977	
BE	3.12	1	3.12	0.051	0.00229	
CD	55.12	1	55.12	0.9	0.3505	
CE	136.12	1	136.12	2.22	0.1467	

DE	465.13	1	465.13	7.6	< 0.0001	
A^2	109.63	1	109.63	1.79	< 0.0001	
B^2	247.79	1	247.79	4.05	0.0536	
C^2	1.55	1	1.55	0.025	0.8746	
D^2	28.55	1	28.55	0.47	0.5001	
E^2	42.47	1	42.47	0.69	0.04117	
Residual	1775.61	29	61.23			
Lack of Fit	1775.61	22	80.71	0.491	1.79	Not significant
Pure Error	69.341	7	20.44			
Cor Total	5737.28	49				

Table 5: Summary of H-WCO biodiesel yield empirical model

Std. Dev.	7.82	R-Squared	0.9690
Mean	74.88	Adj R-Squared	0.9477
C.V. %	10.45	Pred R-Squared	0.9129
PRESS	180.37	Adeq Precision	7.876

3.4 Effect of Process Parameters to WCO Biodiesel Production

3D contour plots were utilized to study the boundary effects between two of the independent parameters while maintaining the remaining variables at optimal levels.

Figure 4a represents the 3D contour plot showing the relationship between reaction temperature and reaction time on WCO biodiesel yield output. Maintaining a catalysts dosage of 1.00 wt%, methanol-to-oil ratio of 9:1 and agitation rate of 200 rpm, increasing the reaction temperature of 60 ºC, and keeping the reaction time at 50 mins increased the biodiesel output upto to 90 %. However, increasing the reaction temperature beyond to 60 ºC while maintaining the same reaction time reduced the biodiesel yield. It is worth to note that higher reaction temperature beyond 60 ºC may favor the backward reaction due to the loss of methanol above the boiling point resulting in low biodiesel generation.

Figure 4b Shows the 3D plot of the effect of reaction temperature and methanol to oil ratio on the WCO biodiesel production while restraining the other input parameters at optimal values. From the plot, increasing the reaction temperature up to 60 ºC while keeping the methanol to oil ration at 9:1 gave the optimal biodiesel yield of 90 %. However, increasing the reaction temperature above 70 ºC reduced the biodiesel yield as a result of temperature above the methanol boiling point which reduces the methanol to oil ration in the process. Figure 4c, shows the 3D plot for the methanol to oil ratio and reaction time for the WCO transesterification process. The plot shows a straight plot for the two effects which means no much effect from the two parameters on the biodiesel yield.

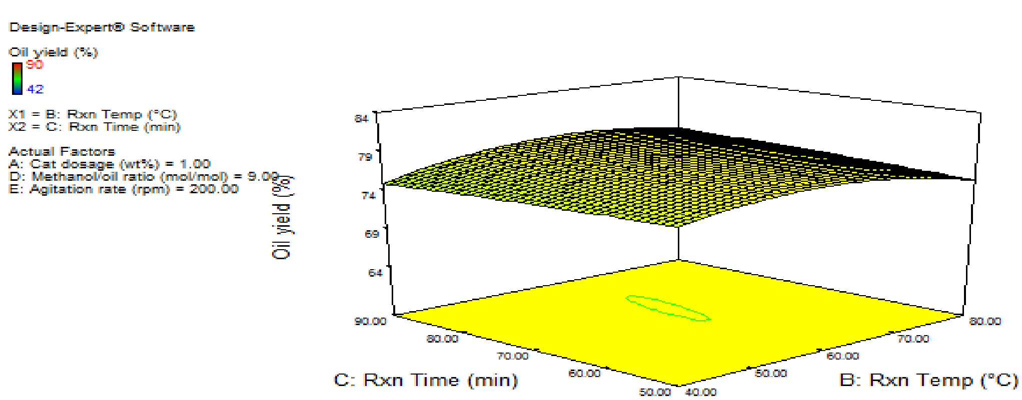

Figure 4a: 3D surface diagram of reaction time, reaction temperature and Biodiesel yields

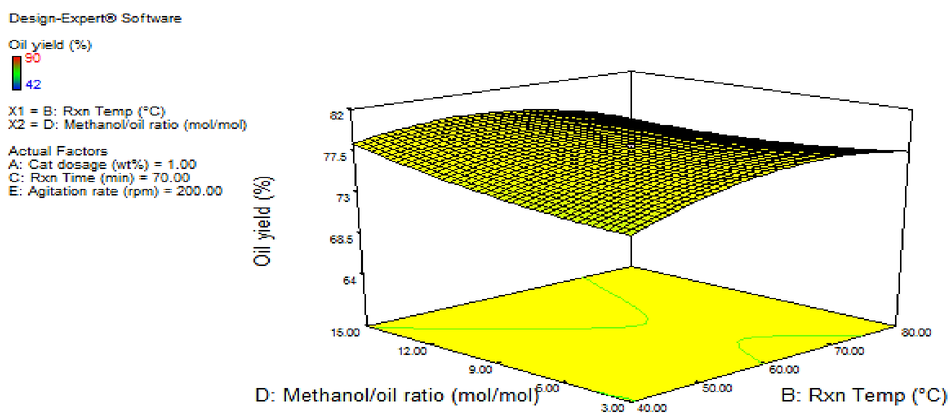

Figure 4b:3D surface diagram of methanol: oil ratio, reaction temperature and Biodiesel yields

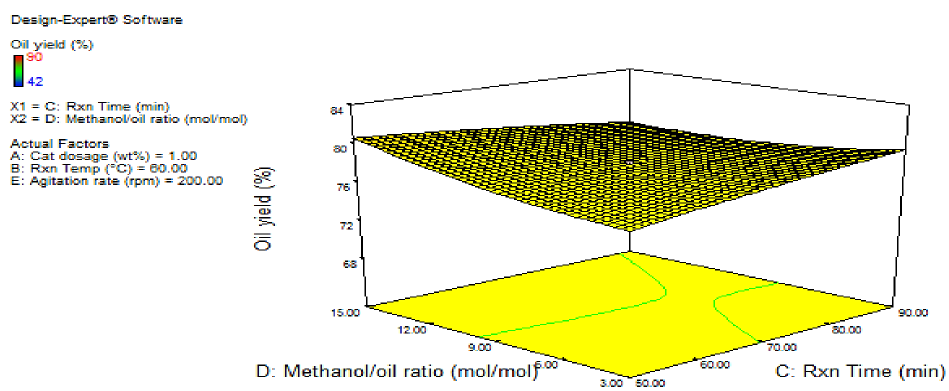

Figure 4c: 3D surface diagram of methanol: oil ratio, reaction time and Biodiesel yields

3.6 ANN / RSM Model Analysis

One of the limitations of RSM is its inability to handle uncontrollable variables. ANN technique employs a feedforward backpropagation algorithm, with different layers of neurons referred to as input, hidden, and output. These algorithms are generally employed as a training technique for training Artificial Neural Networks (ANNs). The tool is considered as a foundation for various neural network models that regulates the network weights to minimalize the difference between predicted output values and actual target outputs (Aghbashlo et al., 2021). The input, hidden, and output layers contains different levels of neurons and utilized TANSIG, TANSIG, and PURLINE activation functions.

Figure 5 designates the result of performing the statistical analysis by utilizing the ANN tool for the data modelling. The ANN model achieved a maximum WCOME yield of 89. 40% when the mean squared error (MSE) approached 0.0059261 while for the RSM model gave the yield value of 87.47%. The determination coefficient (R^2) for the validation ANN model is 0.998 while that of RSM is 0.969. The higher R^2 value (0.998) for the ANN model in comparison to the corresponding values of the RSM model of 0.969 indicate a comparatively better fitness of the ANN model than the RSM model. However, the values of the correlation coefficients ranged $0.95 < R2 < 1.0$ and this implies that more than 95% of the variations in the responses can be explained by the regression model as a mark of good relationship between the RSM predictions and the experimental values (Esonye et al., 2021). The experimental values for the flashpoint, viscosity, cetane number and cloud point for the homogenous process obtained at the optimum conditions were flash point (144 ^oC), Viscosity (6.92 mm^2/s^2), cetane number (42.0) and cloud point (5 ^oC). Figure 6 shows the percentage yield of the experimental value compared with the ANN and RSM predicted values.

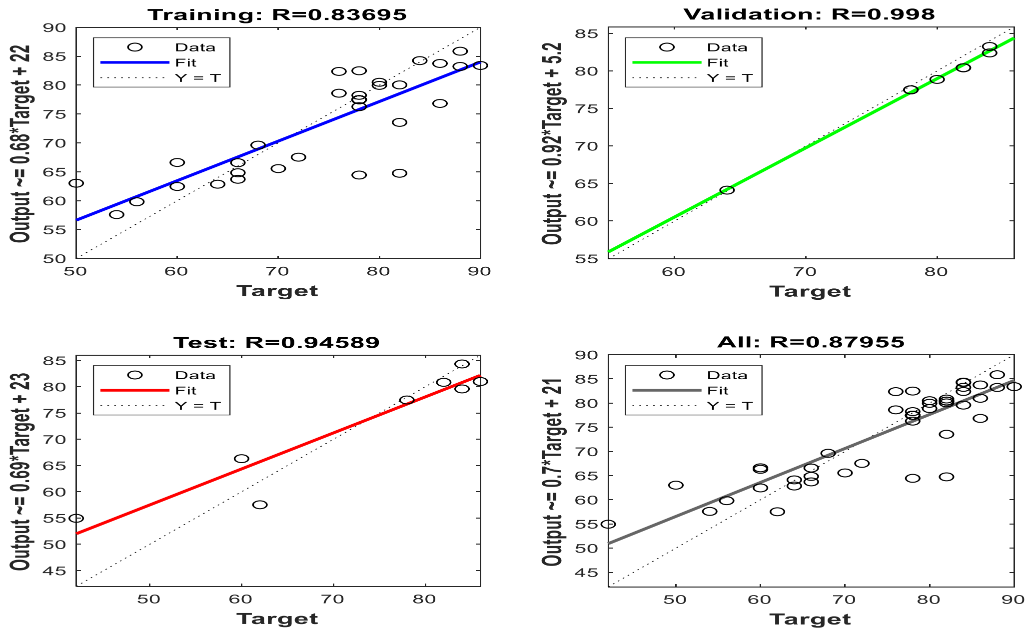

Figure 5: Results of the statistical performance analysis by utilizing the ANN tool for the data modelling.

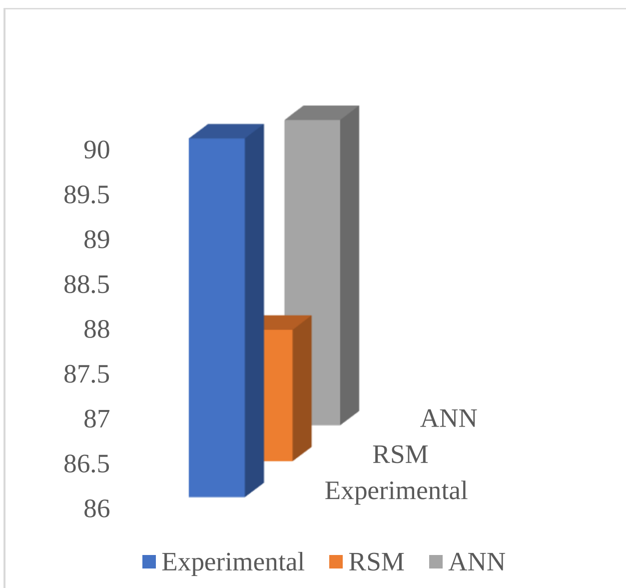

Figure 6: Comparison of experimental, RSM and ANN yield % values.

4. Conclusion

In this present work, biodiesel production through transesterification process and multiple input-output optimization studies were carried out using waste cooking oil and NaOH catalyst. The FFA value of WCO was reduced from 6.61.65 mg KOH/g to 1.18 mg KOH/g through multiple hot water washing and filtration, hence, one step transesterification process was employed for the biodiesel production. The GCMS analysis of WCO biodiesel was conducted to evaluate the saturated and unsaturated components of the fatty acid methyl ester produced. Multiple input- output optimization of the process was achieved by utilizing RSM and ANN mathematical models. The optimum conditions for the biodiesel yield and the corresponding output variables (flash point, viscosity, cetane number and cloud point) were obtained at 50 °C reaction temperature, a 6:1 molar ratio value of methanol-to-oil, a 0.5 wt.% catalyst dosage, a 50 mins value of reaction time and agitation rate of 300 rpm. The experimental biodiesel yield was obtained to be 90.0 % while the predicted biodiesel optimum output for RSM and ANN are 87.47 % and 89.40 % respectively. While the optimal values for the corresponding output parameters were obtained as flash point (144 ºC), viscosity (6.92 mm^2/s), cetane number (42.0) and cloud point (5 ºC). It was observed from the analysis that the RSM and ANN models predicted the biodiesel yield, showing minor errors of 0.003% and 0.005%, respectively when compared to the experimental value, which indicates a significant accuracy level of the models. However, in this present work of optimization of biodiesel production using waste cooing oil, ANN model slightly predicted the biodiesel production process better than RSM. The fuel characteristics of the produced WCO methyl ester conformed to the ASTM D6751 and EN 14214 international standards which confirmed that the product quality.

5. Recommendations

Further studies on the optimization of the biodiesel production should include the tables, figures and statistical analysis of the remaining response parameters considered in this present work**.**

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Nomenclature

C–C-	Carbon bonding
CH_2 –	Methyl group
Na – O –	Sodium /Oxygen bonding
O–H –	Hydroxyl group
SiO-	Silicon oxide
WCO-	Waste cooking oil.
WCOME-	Waste Cooking Oil Methyl Ester.

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