Transesterification via Parametric Modelling and Optimization of Marula (Sclerocarya birrea) Seed Oil Methyl Ester Synthesis

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Abstract: This study investigates Marula (Sclerocarya birrea) seed oil (SBSO) as a novel feedstock for biodiesel production through the transesterification process catalysed by heterogeneous bio-alkali derived from banana (Musa acuminata) peels. Response surface methodology (RSM) and artificial neural network (ANN) tools were used for the modelling and optimization of the process variables. The reaction process parameters considered were methanol/SBSO molar ratio, catalyst loading levels, reaction time and temperature. Central composite design (CCD) was espoused to generate 30 experimental conditions which were deployed in investigating the individual and synergetic effect of the process input variables on Sclerocarya birrea oil methyl ester (SBOME) yield. Appropriate statistical indices were adopted to investigate the predictive aptitude of the two models. Analysis shows that ANN model obtained for the transesterification process has a higher coefficient of determination (R²) of 0.9846 and lower absolute average deviation (AAD) of 0.07% compared to RSM model with R² of 0.9482 and AAD of 0.12%. The process modelling outcome also confirmed ANN performance to be more precise than RSM. At methanol/SBSO ratio of 6:1, catalyst loading level of 2 wt%, process reaction time of 50 min and temperature of 55°C, the experimental maximum SBOME yield was observed to be 96.45 wt % following the ANN predicted yield of 96.45 wt % and RSM predicted yield of 96.65 wt % respectively. The analysed fuel properties of SBOME was found satisfactory within the biodiesel stipulated standard limit(s). The study establishes that SBSO is a good source for biodiesel production and its biodiesel methyl ester is a potential substitute for petroleum diesel and a bioenergy fuel.

Key words: biodiesel production, Sclerocarya birrea seed oil, heterogenous catalyst, modelling, optimization

1 Introduction

The escalation in global energy demand and the awareness of the detrimental impact of fossil fuel combustion on the environment has fostered the quest for alternative energy resources. Biodiesel emerged as the most convenient alternative fuel due to its similarities in properties with petroleum fuel¹. Biodiesel is a renewable, non-toxic and highly biodegradable esters of long chain fatty acids that are derived from lipids of plants and animal sources. It can be used in boilers and internal combustion engines without any modification. Biodiesel is efficient in environmental pollution and global warming mitigation due to its clean burning and eco-friendly nature. Compared to petroleum diesel, biodiesel releases less pollutants and pathogenic gases such as CO₂, CO, SO₂, unburnt hydrocarbons, particulate matters and other aromatic compounds that are dangerous to the environment² and to health. Biodiesel can be used to reduce energy insecurity and improve the rural economic potentials because it can be sourced locally and there are no restrictions in its production. The production process is simple and affordable. The easiest and the most uncomplicated among all the methods is transesterification, which involves a simple chemical reaction of triglycerides and alcohol with the use of a catalyst (acid, base or enzymes) to drive the process.

The transesterification process can either be catalysed by a homogenous or heterogeneous catalyst. Homogenous catalysts have been characterized with various disadvan-
tages wherein heterogenous catalysts are offered as solution. Heterogenous catalysts can be conventional or unconventional. Conventional heterogenous catalysts are derived from inorganic mineral elements while the unconventional are sourced from naturally occurring elements from mineral rich waste biomass materials. Unconventional heterogenous catalysts are receiving industrial attention due to their availability, non-toxicity, recoverability, reusability, eco-friendly, cost effective and easy separation\(^\text{1,3}\). Among other biomass waste materials explored for unconventional base heterogenous catalyst, banana peels have severally been reported as effective heterogenous catalyst in the transesterification of many vegetable oils to biodiesel without further modifications. Its high catalytic activity was reported in the transesterification of esterified palm kernel oil, with a maximum yield of 99.5 wt\(^\%\)\(^\text{4}\). Also reported a high catalytic performance in transesterification of waste cooking oil with maximum yield of 99.9\(^\%\)\(^\text{5}\). In transesterification of soybeans oil with banana peels a maximum yield of 98.95\(^\%\) was reported\(^\text{6}\). The red banana peduncle was used to transesterify *Ceiba pentandra* oil to biodiesel in the experiment conducted by\(^7\)and 98.73% maximum yield was achieved. In the present study, heterogenous catalyst from banana peels was used to investigate the prospect of transesterifying Marula seed oil in biodiesel synthesis.

The transesterification process can best be analysed when the process parameters are modelled and optimized. This allows for the overall effect and the interactions of process variables on the response to be evaluated. Effective statistical modelling tools such as response surface methodology (RSM) and artificial neural network (ANN) system can be applied in simultaneously optimising all the process parameters for the effective prediction of the response. RSM is a collection of mathematical and statistical techniques used for modelling and analysing problems. It is widely applied by researchers in many fields because of its flexibility for various processes. It is predominantly employed in the design of experiments and evaluation of the synergetic effect of process variables and in determination of optimum conditions that generate desired responses.

Additionally, RSM quantifies the relationship between the measurable responses and experimental factors assumed to affect the response. Central Composite Design (CCD) among the RSM packages gives the advantage of optimizing the multifactor problems with optimum number of experimental conditions. It allows for interaction between the experimental process variables within the range of study and also gives a better knowledge of the process with reducing time and cost\(^\text{8,9}\). CCD has been applied to model process parameters such as reaction temperatures, reaction time, catalyst loading levels and methanol-to-oil molar ratios in the transesterification processes of many vegetable oils; neem seed oil\(^\text{10}\), soybean oil\(^\text{11}\), *Brucea javanica* seed oil\(^\text{12}\).

ANN is a data analysis tool and a well-known evolutionary computational method, which imitates the neurological processing capability of the human brain to analyse data. It has been proven as a valuable tool in modelling and simulation of complex and non-linear systems because of its ability to use the learning algorithms to distinguish the relationship between the input and output variables\(^\text{13}\). Its successful application in modelling of various transesterification processes for biodiesel production has been widely reported\(^\text{14-17}\). The study of ANN and RSM models have been carried out in most studies\(^\text{16-18}\) and has always been reported that the ANN model is more accurate in prediction than RSM. However, the overfitting issues associated with neural network can render the validation of the predicted data experimentally unviable. In this work, RSM and ANN models were applied to investigate the transesterification process of *Sclerocarya birrea*(Marula) seed oil conversion to biodiesel.

Research interests have recently been focused on the non-edible source oils for biodiesel synthesis due to the challenges of food vs fuel crises often encountered with the use of edible oils. Apart from the traditional non-edible seed oils like Jatropha, karanja, rubber, mahua, sea mango, neem, moringa, jujuba, calophyllum, yellow oleander etc, extensive efforts have been made in the discovering of new indigenous non-edible and underutilized oil seeds for biodiesel production which include; *Manilkara zapota* L. seed oil\(^\text{19}\), *Sterculia foetida* oil\(^\text{20}\), Norouzak seed oil\(^\text{21}\), *Terminalia bellierica* seed oil\(^\text{22}\), *Argemone mexicana* seed oil\(^\text{23}\), Macadamia seed oil\(^\text{24}\), *Reutealis trisperma* oil\(^\text{25}\), *Ceiba pentandra* seed oil\(^\text{26}\), purslane seed oil\(^\text{27}\) and so on. Another of this kind is the Marula (*Sclerocarya birrea*) seed oil which is abundantly available and indigenously sourced plant in South Africa and other sub-savanna regions of the world.

*Sclerocarya birrea*-spp *caffra*, popularly known as Marula is an indigenous deciduous savanna tree that belongs to the *Anacardiaceae* family. It is widely distributed throughout sub-Saharan Africa, from the tropical, central to Southern Africa. It normally grows up to 18 - 20 metres in height and well adapted to a woodland habitat on a sandy loam soil and are leafless during winter\(^\text{28}\). The fruits are edible and yellow in colour with aplain tough skin and glutinous flesh which encloses 2-3 white kernels which are rich in oil and protein\(^\text{29}\). The nut comprises of 90% of shell and only 10% of kernel. The seeds contain up to 56% oil per kernel and the energy value of 2699 to 2703 kJ per 100 g kernel\(^\text{30}\). The seed oil has been found to contain mainly fatty acid of oleic, palmitic, stearic and linoleic acid which are excellent for biodiesel production. The seeds have not been utilised for any major economic purposes except for traditional medicine, alcoholic creams and cosmetics. Hence, this underutilized seed oil with high
level of unsaturated fatty acids could be considered a good precursor for biodiesel production.

The aim of this study therefore is to investigate the feasibility of biodiesel synthesis from S. birrea oil via the transesterification process modelled by RSM and ANN systems. The production process was examined using calcined Musa acuminata peels (CMAPA) heterogenous catalyst. To the best of our knowledge, there has not been any such novel work reported on biodiesel production from S. birrea seed oil. Therefore, the properties of its methyl ester were studied and compared with the ASTM D6751 and EN 14214 biodiesel standards to examine its viability.

2 Materials and Methods

2.1 Materials

The crude S. birrea seed oil was supplied by United scientific laboratory together with all chemicals used in this study which include: methanol (98% purity), ethanol (98% purity), potassium iodide, hydrochloric acid, wijn’s solution (monochloride solution), diethyl ether, phenolphthalein, cyclohexane and chloroform which were all of analytical grades.

2.2 Bio-alkaline heterogenous catalyst preparation

Heterogenous catalyst prepared from banana peels and its characterization has already been studied and reported\(^6,^7,^31\), therefore characterisation process was not considered further in this study. A similar preparation process was adopted. Briefly, the waste banana peels (Musa acuminata) were washed thrice with distilled water and dried in the oven for 24 h at 80°C. The dried materials were combusted in open air and the ash obtained were further calcined in a muffle furnace at 700 °C in open air and the ash obtained were further calcined in an oven for 24 h at 80 °C. The dried materials were combusted in open air and the ash obtained were further calcined in a muffle furnace at 700 °C for 4 h. Calcined Musa acuminata peels ash (CMAPA) was pulverized with the aid of an agate mortar and pestle, and then packed into an air-tight container and was used without any further modification.

2.3 Quality characterization of sclerocarya birrea oil

2.3.1 Physicochemical properties of SBSO

In order to ascertain the quality and the suitability of oils for any purpose, physico-chemical properties are vital decisive factor. The physicochemical properties such as kinematic viscosity, density, iodine value, acid value, FFA, saponification, cetane number, calorific value, API and diesel index were determined following standard methods, while the cloud point, cold filter plugging point (CFPP) and oxidative stability (OS) were determined following the proposal of\(^32,^33\) for the SBSO and SBOME and were all compared with American, European and South African standards (ASTMD 6751, EN 14214 and SANS 833:2012).

2.3.2 Fourier transform infrared spectrum (FT-IR) analysis

Infrared radiation analysis was conducted to obtain the corresponding spectra, which were used to determine the functional groups present in the oil and the biodiesel produced. The FT-IR spectra were acquired at the range of 4000 – 400 cm\(^{-1}\) using Fourier Transform spectrometer (PerkinElmer, Waltham, USA).

2.3.3 Gas chromatography analysis

The analysis of the composition of the fatty acids was performed using Gas Chromatograph (GCMS-QP2010 Ultra, Shimadzu) coupled with mass spectrometer (GC-MS), with column capillary (RXT-5, 30 m ×, 0.25 mm × and 0.25 μm). The oven temperature was set at 70°C for 1.5 min before ramping up to 10°C/min to 320°C and maintained at 10 min. Helium gas was used as a carrier gas with a flow rate of 60 (mL/min) and the sample volume of 1.0 μl was injected using a split-less mode at injection temperature of 220°C

2.4 Experimental design for the transesterification process by RSM

Central composite design (CCD) was adopted for the experimental design of this work. A four factor five level design was used to generate 30 experimental runs. The CCD design include 16 factorial points, 8 axial points and 6 central points to supply information regarding the interior of the experimental region, in order to confirm the possibility of evaluating the interactive effect of the process variables. Table 1 shows the process input parameters and their ranges viz methanol/SBSO (4:1 – 12:1), catalyst loading level (1.0 – 5.0), reaction time (40 – 80) and reaction temperature (50 – 70°C). Table 2 shows the respective actual and coded level factors of independent variables. Zero (0) value represents the centre point for the variables while -1 and +1 represent the lower and upper value of the four process variables. -2 and +2 represent the lowest and highest value suggested by the model for every

| Factors                  | Units       | Coded factor levels |
|--------------------------|-------------|---------------------|
|                         |             | -2 | -1 | 0   | +1 | +2  |
| Methanol/SBSO molar ratio| 4:1         | 6:1| 8:1| 10:1| 12:1|
| Catalyst Loading         | wt%         | 1.0| 2.0| 3.0 | 4.0| 5.0 |
| Time                     | Min         | 40 | 50 | 60  | 70 | 80  |
| Temperature              | °C          | 50 | 55 | 60  | 65 | 70  |
parameter within the range studied. The quadratic polynomial model terms of the variables were fitted through multiple regressions. Both analysis of variance (ANOVA) and the significance test at 95% confident level were applied to establish the features of the model. The second order mathematical equation that describes the fitness of the polynomial response model is given in Equation 1.

\[
Y = Q_0 - Q_1 X_1 - Q_2 X_2 - Q_3 X_3 - Q_4 X_4 + Q_{12} X_1 X_2 + Q_{13} X_1 X_3 + Q_{14} X_1 X_4 + Q_{23} X_2 X_3 + Q_{24} X_2 X_4 + Q_{34} X_3 X_4 + Q_{11} X_1^2 + Q_{22} X_2^2 + Q_{33} X_3^2 + Q_{44} X_4^2
\]

(1)

Where \(Y\) is the SBOME yield (the predictive response), \(Q_0\) is the intercept value, \(Q_1, Q_2, Q_3, Q_4\) are the independent coefficients, \(Q_{12}, Q_{13}, Q_{14}, Q_{23}, Q_{24}, Q_{34}\) are the interaction coefficients, and \(X_1, X_2, X_3, \) and \(X_4\) represent the independent variables. The synergetic effect of the process variables on the response are demonstrated on the surface plot representation.

### 2.5 ANN modelling of the transesterification process

ANN are trained to execute a function by data connec-

### Table 2: Factors and yield predicted by RSM and ANN.

| Standard order Run | \(X_1\) | \(X_2\) | \(X_3\) | \(X_4\) | SBOME (wt\%) | RSM Predicted | ANN Predicted |
|--------------------|---------|---------|---------|---------|-------------|--------------|--------------|
| 10                 | 10(1)   | 2(-1)   | 50(-1)  | 65(1)   | 89.23       | 90.07        | 89.23        |
| 29                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 89.63       | 88.16        | 88.07        |
| 14                 | 10(1)   | 2(-1)   | 70(1)   | 65(1)   | 84.75       | 83.60        | 84.75        |
| 2                  | 10(1)   | 2(-1)   | 50(-1)  | 55(-1)  | 88.60       | 87.79        | 88.60        |
| 11                 | 6(-1)   | 4(1)    | 50(-1)  | 65(1)   | 88.37       | 87.74        | 88.37        |
| 3                  | 6(-1)   | 4(1)    | 50(-1)  | 55(-1)  | 88.80       | 89.07        | 88.13        |
| 8                  | 10(1)   | 4(1)    | 70(1)   | 55(-1)  | 90.10       | 90.86        | 91.00        |
| 7                  | 6(-1)   | 4(1)    | 70(1)   | 55(-1)  | 93.90       | 92.98        | 93.90        |
| 4                  | 10(1)   | 4(1)    | 50(-1)  | 55(-1)  | 84.45       | 82.94        | 84.45        |
| 21                 | 8(1)    | 3(0)    | 40(-2)  | 60(0)   | 86.75       | 88.38        | 87.40        |
| 28                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 87.00       | 88.16        | 88.07        |
| 15                 | 6(-1)   | 4(1)    | 70(1)   | 65(1)   | 83.00       | 82.93        | 83.00        |
| 20                 | 8(0)    | 5(2)    | 60(0)   | 60(0)   | 86.45       | 87.62        | 86.45        |
| 24                 | 8(0)    | 3(0)    | 60(0)   | 70(2)   | 80.30       | 81.04        | 80.30        |
| 12                 | 10(1)   | 4(1)    | 50(-1)  | 65(1)   | 88.90       | 87.97        | 89.11        |
| 16                 | 10(1)   | 4(1)    | 70(1)   | 65(1)   | 87.45       | 87.17        | 88.20        |
| 18                 | 12(2)   | 3(0)    | 60(0)   | 60(0)   | 90.10       | 90.88        | 90.10        |
| 17                 | 4(-2)   | 3(0)    | 60(0)   | 60(0)   | 95.30       | 95.48        | 95.30        |
| 27                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 88.25       | 88.16        | 88.07        |
| 5                  | 6(-1)   | 2(-1)   | 70(1)   | 55(-1)  | 94.85       | 94.90        | 94.85        |
| 30                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 88.10       | 88.16        | 88.07        |
| 22                 | 8(0)    | 3(0)    | 80(2)   | 60(0)   | 86.50       | 85.83        | 86.50        |
| 6                  | 10(1)   | 2(-1)   | 70(1)   | 55(-1)  | 89.50       | 90.05        | 89.50        |
| 19                 | 8(0)    | 1(-2)   | 60(0)   | 60(0)   | 91.85       | 91.63        | 91.85        |
| 26                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 88.40       | 88.16        | 88.07        |
| 1                  | 6(-1)   | 2(-1)   | 50(-1)  | 55(-1)  | 96.45       | 96.65        | 96.45        |
| 13                 | 6(-1)   | 2(-1)   | 70(1)   | 65(1)   | 80.65       | 82.08        | 79.89        |
| 9                  | 6(-1)   | 2(-1)   | 50(-1)  | 65(1)   | 94.20       | 92.56        | 94.20        |
| 25                 | 8(0)    | 3(0)    | 60(0)   | 60(0)   | 87.55       | 88.16        | 88.07        |
| 23                 | 8(0)    | 3(0)    | 60(0)   | 50(-2)  | 88.60       | 88.82        | 88.60        |

Where \(X_1\) - methanol-to-oil ratio, \(X_2\) - catalyst loading, \(X_3\) - time, \(X_4\) - temperature

\(X_1 - \text{methanol-to-oil ratio}, X_2 - \text{catalyst loading}, X_3 - \text{time}, X_4 - \text{temperature}\)
tion or weight adjustment between elements until the input generates the output. It consists of three layers which are connected to each other; the input layer, hidden layers and output layer. The input layer obtains data outside the network and delivering to the hidden layer. The hidden layer interconnected the neurons for pattern identification and adjusts the weights on the connection based on relevant information interpreted which sends the result to the output layer in order to generate the output. The neurons contain different functions and variables including non-linear and linear transfer functions which determine the output result. ANN is advantageous and attractive in its capacity to model complex and non-linear relationships in a process.

In this study, the precision of this modelling tool was obtained by including all the experimental data generated by the CCD matrix. A total number of 30 data sets were used and the process input parameters investigated were methanol-to-oil molar ratio, catalyst loading levels, process reaction time and temperature. The ANN model was developed using MATLAB (2015a, version 8.5.0). To obtain the desired model, the data set is usually split into three subsets, where 70% of the processed data is used for training, 15% for testing the reliability of the model and the remaining 15% is for validation. A two-layer feedforward back propagation (FFBP) network was used with Levenberg-Marquardt training algorithm (trainlm). The hidden layer was optimized with different numbers of neurons alternating from 5, 10 and 15. The tangent sigmoid (tansig) transfer function was used for the input hidden layer while the output hidden layers were optimized with different transfer functions (tansig, logsig, and purelin) in order to generate effective network topology for adequate prediction of SBOME yield. Each network topology was evaluated with several number of iterations until the lower value of the mean-square-error (MSE) with the highest correlation coefficient (R) approaching one was identified. The general forms of each transfer function used in this study are shown below:

Tangent sigmoid function;  
\[ f(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}} \]  
(2)

Log sigmoid function;  
\[ f(t) = \frac{1}{1 + e^{-t}} \]  
(3)

Purelin function;  
\[ f(t) = t \]  
(4)

2.6 Statistical appraisal of the developed models

The efficacy of the two models were statistically evaluated. The assessment was done using Equations (5)–(12) to determine the parameters such as R, \( R' \), MSE, SEP, MAE and AAD. The evaluation was done based on the least error values (RMSE, SEP, MAE and AAD) obtained and the highest correlating coefficient factors \( R_s \). The obtained results were used to compare the performance and efficiencies of the two modelling tools in determining the best in terms of SBOME prediction. The accuracy of each model was also evaluated by plotting the predicted values obtained with the actual experimental values on a straight line.

Correlation coefficient
\[ R = \frac{\sum_{i=1}^{q}(Z_{a,i} - Z_{a,m})(Z_{p,i} - Z_{p,m})}{\sqrt{\sum_{i=1}^{q}(Z_{a,i} - Z_{a,m})^2} \sum_{i=1}^{q}(Z_{p,i} - Z_{p,m})^2} \]  
(5)

Coefficient of determination
\[ R^2 = 1 - \frac{\sum_{i=1}^{q}(Z_{a,i} - Z_{p,i})^2}{\sum_{i=1}^{q}(Z_{p,i} - Z_{a,m})^2} \]  
(6)

Adjusted \( R^2 \)
\[ Adjusted \ R^2 = 1 - \left[ (1 - R^2) \times \frac{q - 1}{q - h - 1} \right] \]  
(7)

Mean square error
\[ MSE = \frac{1}{q} \sum_{i=1}^{q}(Z_{a,i} - Z_{p,i})^2 \]  
(8)

Root mean square error
\[ RMSE = \sqrt{\frac{1}{q} \sum_{i=1}^{q}(Z_{a,i} - Z_{p,i})^2} \]  
(9)

Mean absolute error
\[ MAE = \frac{1}{q} \sum_{i=1}^{q} | (Z_{a,i} - Z_{p,i}) | \]  
(10)

Standard error of prediction
\[ SEP = \frac{RMSE}{Z_{a,m}} \times 100 \]  
(11)

Average absolute deviation
\[ AAD = \frac{100}{q} \sum_{i=1}^{q} \left| \frac{(Z_{a,i} - Z_{p,i})}{Z_{a,i}} \right| \]  
(12)

Where Correlation coefficient is \( R \), coefficient of determination \( R^2 \), mean-square-error \( MSE \), root mean square error \( RMSE \), mean absolute error \( MAE \), standard error of prediction \( SEP \) and average absolute deviation \( AAD \). \( q \) is the number of experiment data, \( Z_{a,i} \) is the experimental value, \( Z_{p,i} \) is the predicted value, \( Z_{a,m} \) is the experimental mean value, \( Z_{p,m} \) is the predicted value and \( h \) is the number of input variables.

2.7 Transesterification of SBSO with the biomass prepared heterogeneous catalyst

The synthesis of the biodiesel was carried out by reacting the SBSO with methanol in the presence of the calcined banana peels ash (CMAPA) as catalyst in a 250 mL three necked spherical flask reactor, fitted with a reflux condenser and a thermometer on a magnetic stirrer hot plate as shown in Fig. 1. Reaction commences by discharging a specified amount of SBSO into the reactor and allowed to heat up to 60°C. A desired amount of methanol was added to the oil in the reactor followed by the addition of a specified quantity of catalyst after 5 mins. The reaction was monitored following the design guide in Table 2. At the end of each reaction condition, the resulting content was trans-
ferred into the separating funnel and allowed to stand overnight for gravitational settling and phase separation. A three-layered phase was formed; the crude biodiesel, glycerol and catalyst. The glycerol and catalyst were drawn off and the crude biodiesel left was purified by wet washing with warm distilled water and dried further by heating to 100°C using a heating mantle. Thus, this process helps in removing all the contaminants that was remaining in the crude biodiesel product after production including leached metals from the bio-alkaline catalyst, methanol, glycerol and water. The purified Marula oil methyl ester (SBOME) yield was determined gravimetrically as described by Equation 13. The purified SBOME was then evaluated for physicochemical properties.

$$SBOME(\text{wt}%) = \frac{\text{weight of SBOME produced}}{\text{weight of SBSO used}} \times 100 \quad (13)$$

3 Results and Discussion
3.1 Physicochemical properties of SBSO and SBOME

The physicochemical properties of *Sclerocarya birrea* oil and its methyl ester were determined and the results are presented in Table 3. The properties of SBSO showed that it is a potential feedstock for biodiesel production. Though the properties of SBSO such as iodine value and cetane number were within the international and South African specified limits, its viscosity and acid value were higher compared to the standards. The viscosity of SBSO was found to be 17.5 mm²/s, which implies that it cannot be used directly in a combustion engine. The acid value of SBSO was 4.35 mg KOH/g with the corresponding FFA of 2.17%, therefore a one-step transesterification was used in its conversion.

The fuel properties determined are comparable with the ASTM D6751, EN 14214 and SANS 833 standards, which implies that SBOME is a viable biodiesel. The fuel properties of SBOME are also presented in Table 3. Key properties such as kinematic viscosity of SBOME was 4.37 mm²/s, which falls within the American, European and South African standard limits, as higher kinematic viscosity causes operational problems in engine due to poor fuel atomization. The density of SBOME was 0.882 kg/m³ and acid value was 0.423 mg KOH/g which are within the standard limits. The iodine value measures the degree of unsaturation in a fatty acid mixture. The iodine values obtained for SBOME was 78.35 g I²/100 g, which is satisfactorily within EN 14214 and SANS 833 standard specifications.

Cetane number is an important property considered in methyl ester selection. It is the ability of a fuel to ignite after injection. A higher value of cetane number indicates better ignition quality of a fuel and good engine performance. Adequate cetane number is needed to ensure good cold starting properties and white smoke reduction. The cetane number obtained for SBOME was 58.38 MJ/kg, which was higher than the minimum limit specified by ASTM D6751, EN 14214 and SANS 833. Calorific value obtained was 40.72 MJ/kg and oxidative stability which has a technical effect on the application of biodiesel was 4 h and it was within the limit of American standards but below the EN 14214 and SANS 833 minimum specifications.

The cold flow property is another important property to be considered in methyl ester quality. It affects the opera-
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bility of the fuel during cold weather conditions. Biodiesel properties at low temperature are mainly dependent on saturated fatty acids. Cloud point is the most important among the cold flow parameters of biodiesel. It is the temperature at which liquid fatty material becomes cloudy due to crystal formation in a specified condition. Saturated compounds have a higher melting point than unsaturated compounds. When in mixture, saturated compounds tend to crystallize at high temperatures than unsaturated, leading to higher cloud point. The CP obtained in this study was 2°C, which falls within the ASTM range.

Cold filter plugging point (CFPP) is another important cold flow parameter in biodiesel, it measures the capability of biodiesel to operate at low temperature. This is the temperature at which fuel is unable to pass through the filter due to the formation of crystal agglomeration. Increase in long chain saturated fatty acids tend to increase the cold filter plugging point of the biodiesel product. Moreover, the lower the CFPP value, the more difficult it is to crystallise biodiesel. The CFPP obtained for SBOME was 0.5°C, which is within the American standard limit of 5 max. Thus, the obtained value is high when compared to the methyl esters obtained from other vegetable oils such as sunflower, grape and soybean which are highly unsaturated. However, the specific range of values for CFPP is not specified in EN 14214 standards due to uncertainty in temperature limit of different climates in various countries. Other properties such as diesel index, American petroleum index (API) and Aniline were also found closed to the range stipulated by American standard.

3.2 Fatty acids composition of SBSO and SBOME

GC-MS was employed to analyse and quantify the fatty acids composition of SBSO and SBOME and the results are shown in Table 4. Among the fatty acids identified, oleic acid which is unsaturated was found to be dominant with the value of 72.8% in SBSO and 73.2% in SBOME. The dominant among the saturated fatty acids are palmitic acid with a value of 12.3% in SBSO and 13.2% in SBOME, followed by stearic acid with a value of 7.20% in SBSO and 8.20% in SBOME. This is in line with the values reported in literature. Among other saturated compounds present in SBOME, traces of odd chains saturated compounds were also indicated such as pentadecyclic acid (C15:0) (0.08%) and margaric acids (C17:0) (0.68%) while nonadecylic acid (C19:0) (0.41) was found to be contained in SBSO. These compounds of fatty acid are rare in most vegetable oils. The total percentage of saturated and unsaturated fatty acids in SBSO was 20.39:79.61 while in SBOME was 24.20:75.80. High saturated fatty acids in methyl ester tends to influence the cold flow properties by increasing the temperature to which it occurs. According

Table 3 Properties of SBSO and SBOME with biodiesel standards.

| Properties                | Units | SBSO     | SBOME     | ASTM D6751 | EN 14214 | SANS 833 |
|---------------------------|-------|----------|-----------|------------|----------|----------|
| Colour                    | -     | Pale yellow | Golden yellow |            |          |          |
| Moisture content          |       | 0.02     | 0.01      | < 0.03     | 0.02     | 0.05     |
| Density @25°C             | kg/m³ | 0.938    | 0.882     | 0.86 – 0.90 | 0.85     | 0.86 – 0.9 |
| Kinematic viscosity @40°C | mm²/s | 17.5     | 4.37      | 1.9 – 6.0  | 3.5 – 5.0 | 3.5 – 5.0 |
| Acid value                | mg KOH/g | 4.348  | 0.423     | 0.5 max    | 0.5 max  | 0.5 max  |
| Free fatty acid           | %     | 2.174    | 0.212     | 0.25 max   | –        | –        |
| Iodine value              | g I₂/100 g | 84.4   | 78.35     | –          | ≤ 120    | 140 max  |
| Saponification value      | mg KOH/g | 184    | 183.7     | –          | –        | –        |
| Calorific value           | MJ/kg | 40.62    | 40.72     | –          | –        | –        |
| Cetane number             |       | 56.97    | 58.38     | 47 min     | 51 min   | 51 min   |
| Flash point               | °C    | 232      | ND        | 130 min    | 120 min  | –        |
| Cloud point               | °C    | ND       | 2         | –3 to 12   | –        | –        |
| Cold Filter Plugging Point (CFPP) | °C     | ND | 0.5     | 5 max     | –     | -4 to +3 |
| Oxidative stability       |        | ND       | 4.0       | ≥ 3        | ≥ 6      | 6 min    |
| Diesel index              |       | ND       | 67.19     | 50.4       | –        | –        |
| API                       |       | ND       | 28.93     | 36.95      | –        | –        |
| Aniline                   | °F    | ND       | 232       | 331        | –        | –        |

ND= Not determined
to long or branch chain alcohol such as butanol and iso-propanol are preferable in converting oils with increasing saturated fatty acids content in order to reduce their effects on the cold flow properties.

3.3 IR spectra of SBSO and SBOME

SBSO and SBOME IR spectra are shown on Fig. 2(a, b). Similar peaks are demonstrated on the two spectra between 4000 and 1742 cm\(^{-1}\). The presence of peaks 2922 cm\(^{-1}\) and 2853 cm\(^{-1}\) confirms the stretching vibrations of CH\(_3\) and CH\(_2\) bonds of asymmetric and symmetric vibration respectively. The strong peaks at 1744 cm\(^{-1}\) and 1742 cm\(^{-1}\) in both spectra respectively indicate a typical stretching vibration of the carbonyl group (C=O) present in the triglycerides. It can be noticed that the peak at 1463 cm\(^{-1}\) in SBSO broke up into two distinct signal of 1460 cm\(^{-1}\) and 1435 cm\(^{-1}\) in SBOME, this may be attributed to the deformation vibration of O-CH\(_3\) group. The band region between 1377 cm\(^{-1}\) and 1361 cm\(^{-1}\) for both SBSO and SBOME is ascribable to the stretching vibration of C=O group showing the conversion of triglyceride to esters, and since there is no change in peak from the two spectra, it therefore implies that there were no impurities present in SBOME\(^{38}\). The characteristic region of 1195 – 722 cm\(^{-1}\) in both spectra which is more in the SBOME spectrum, indicate a typical stretching and rocking vibration of carboxyl (C-O) group which shows the presence of ester\(^{39}\). The split shown on SBOME spectrum between 1195 cm\(^{-1}\) and 1169 cm\(^{-1}\) indicated the replacement of CH\(_2\)O in triglyceride by CH\(_3\)O in methyl ester. This is also in line with the ones reported by\(^{40, 41}\).

3.4 Parameters optimization of the transesterification process by RSM modelling

The result of the transesterification of SBSO to SBOME is displayed in Table 2. The methyl ester yield varied from the lowest at 83.00 wt\% to the highest at 96.45 wt\%. The lowest yield was obtained at methanol-to-oil molar ratio of 8:1, catalyst loading of 3.0 wt\%, reaction time of 60 min and temperature of 60\(^\circ\)C. The maximum yield was obtained at methanol-to-oil molar ratio of 6:1, catalyst loading of 2.0 wt\%, reaction time of 50 min and temperature of 55\(^\circ\)C. The modelling equation obtained as a result of the application of multiple regression, which shows the correlation between the process parameters and response (SBOME yield) is described in Equation 14.

\[
Y(\text{wt}\%) = 88.16 - 1.15X_1 - 1.00X_2 - 0.6375X_3 - 1.95X_4 + 0.6813X_1X_4 + 1.00X_2X_3 + 1.59X_3X_4 + 1.42X_1^2 + 1.02X_2^2 + 1.26X_3^2 + 0.3685X_4^2 - 0.2627X_1^2 - 0.8065X_4^2
\]

(14)

Table 4 Fatty acid composition of SBSO and SBOME.

| Methyl esters | Molecular Formula | Structure | SBSO | SBOME |
|---------------|-------------------|-----------|------|-------|
| Pentadecylic acid | C\(_{15}\)H\(_{30}\)O\(_2\) | C15:0 | – | 0.08 |
| Palmitic acid | C\(_{16}\)H\(_{36}\)O\(_2\) | C16:0 | 12.3 | 13.2 |
| Margaric acid | C\(_{17}\)H\(_{34}\)O\(_2\) | C17:0 | – | 0.68 |
| Steraric acid | C\(_{18}\)H\(_{36}\)O\(_2\) | C18:0 | 7.20 | 8.20 |
| Nonadecylic acid | C\(_{19}\)H\(_{38}\)O\(_2\) | C19:0 | 0.41 | – |
| Arachidic acid | C\(_{20}\)H\(_{40}\)O\(_2\) | C20:0 | 0.48 | – |
| Behenic acid | C\(_{22}\)H\(_{44}\)O\(_2\) | C22:0 | – | 1.60 |
| Lignoceric acid | C\(_{24}\)H\(_{48}\)O\(_2\) | C24:0 | – | 0.44 |
| Total saturated | | | 20.39 | 24.2 |
| Palmitoleic acid | C\(_{16}\)H\(_{30}\)O\(_2\) | C16:1 | – | 1.10 |
| Oleic acid | C\(_{18}\)H\(_{36}\)O\(_2\) | C18:1 | 72.8 | 73.2 |
| Linoleic acid | C\(_{18}\)H\(_{32}\)O\(_2\) | C18:2 | 6.20 | 1.20 |
| Linolenic acid | C\(_{18}\)H\(_{36}\)O\(_2\) | C18:3 | 0.61 | 0.30 |
| Total unsaturated | | | 79.61 | 75.8 |
| DU | | | 77.3 |
| LCSF | | | 8.70 |

DU: Degree of unsaturation  
LCSF: Long chain saturated factor
Where \( Y \) is SBOME in (wt\%), \( X_1, X_2, X_3 \) and \( X_4 \) are the independent terms which denote Methanol-to-oil, catalyst loading, reaction time and reaction temperature. \( X_1X_2, X_1X_3, X_2X_3, X_3X_4 \) are the interactive terms and \( X_1^2, X_2^2, X_3^2, X_4^2 \) are the quadratic terms.

Equation 14 shows the impact of terms on the response, the positive and negative signs of the regression coefficients indicate the nature of influence of the modelling terms on the response. Analysis of variance (ANOVA) showing the significance and the fitness of the quadratic model and the influence of the individual significance term and their interactions on the response is presented in Table 5. The model \( F \)-value of 19.60 and \( p \)-value of < 0.0001 shows that the model is statistically significant at 95% confidence level \((p < 0.05)^{42}\). All the terms are significant except the quadratic terms of catalyst and time \((X_2^2 \) and \( X_3^2 \)). The good fit of the regression equation developed could be measured based on the obtained values of \( R^2 \) (0.9482) and adjusted \( R^2 \) (0.8998). This implies that the model was significant and capable of predicting 94% of the total dataset in close relation with the experimental values.

The value of adjusted \( R^2 \) (0.8998) is in alliance with the \( R^2 \) (0.9482), which indicates goodness of the model fit. The predicted \( R^2 \) of 0.7406 is in reasonable agreement with the adjusted \( R^2 \) of 0.8998. The lower value of coefficient of variance (CV) of 1.39% shows the high level of consistency with minimal variations between the experimental and the predicted value. A value greater than 4 is desired for adequate precession value to measure the signal-to-noise ratio. In this case, the adequate precession value of 17.98 obtained was sufficient for the model to be used to pilot the design space. The non-significant lack of fit, \( p \)-value of 0.1776 relative to pure error implies the significance and goodness of fit of the model. RSM’s predicted SBOME yield is presented in Table 2. Numerical optimization conditions obtained by setting the constraints in range at the desired levels to enhance the maximum yield was methanol-to-oil ratio of 6:1, catalyst loading of 2.0 wt\%, reaction time of 50 mins and temperature of 55°C, with the yielded experimental value of 96.45 and the software predicted value of 96.65 wt\%.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{IR_spectra}
\caption{IR spectra of (a) SBSO and (b) SBOME.}
\end{figure}
3.5 Interactive effects of variables on SBOME yield

The interaction effect of variables such as methanol-to-oil ratio, catalyst loading, reaction time and reaction temperature on SBOME yield are depicted on the surface plots in Fig. 3 (a-f). Figure 3a depicts the synergetic interaction of molar ratio of methanol-to-oil and catalyst loading on SBOME synthesis. The figure shows that both methanol and catalyst have significant effect on the yield. SBOME yield increase as the methanol ratio and the catalyst loading decrease. The influence of methanol ratio was found stronger than the catalyst loading. The observation is also supported by the ANOVA presented in Table 5 with the methanol p-value (0.0003). The molar ratio of alcohol/oil is one of the vital factors affecting the biodiesel yield in the transesterification process. To enhance effective mixing and heat transfer interface, theoretical stoichiometric ratio of the transesterification reaction indicates that three moles of methanol is required for one mole of triglyceride. As the transesterification reaction is reversible in nature, methanol should be in excess in order to drive the equilibrium reaction in favour of the forward reaction which is the biodiesel yield. On the other hand, a higher molar ratio of alcohol hinders the separation process due to increase in solubility, which favours the backward reaction leading to low biodiesel yield\(^{31}\). Moreover, dilution of catalyst through excess alcohol is another issue that needs to be avoided to make effective the overall economics, especially when the recovery of the excess alcohol is considered. In this work, the ratio of methanol/oil was studied between 4:1 to 12:1 which is higher than the theoretical ratio of 3:1. FAME yield was found to increase as the molar ratio decreases up to the value of 6:1. A decrease in yield occurred beyond this ratio and the lowest yield was observed at the ratio of 8:1. The prime yield was obtained at the ratio of 6:1, the selected range (4:1 - 12:1) was adequate for all the transesterification reaction of the SBSO.

**Table 5** Test of significance and ANOVA.

| Source                  | Coefficient estimation | Sum of Squares | df | Mean Square | F-value | p-value |
|-------------------------|------------------------|----------------|----|-------------|---------|---------|
| Model                   | 88.16                  | 413.29         | 14 | 29.52       | 19.60   | <0.0001 |
| Linear intercept        |                        |                |    |             |         |         |
| Methanol-to-oil ratio (X,) | -1.15                 | 31.83          | 1  | 31.83       | 21.13   | 0.0003  |
| Catalyst loading (X,)   | -1.00                  | 24.12          | 1  | 24.12       | 16.01   | 0.0012  |
| Time (X,)               | -0.6375                | 9.75           | 1  | 9.75        | 6.48    | 0.0224  |
| Temperature (X,)        | -1.95                  | 90.87          | 1  | 90.87       | 60.33   | <0.0001 |
| Interaction             |                        |                |    |             |         |         |
| X1X2                    | 0.6813                 | 7.43           | 1  | 7.43        | 4.93    | 0.0422  |
| X1X3                    | 1.00                   | 16.08          | 1  | 16.08       | 10.68   | 0.0052  |
| X1X4                    | 1.59                   | 40.51          | 1  | 40.51       | 26.90   | 0.0001  |
| X2X3                    | 1.42                   | 32.09          | 1  | 32.09       | 21.31   | 0.0003  |
| X2X4                    | 0.6900                 | 7.62           | 1  | 7.62        | 5.06    | 0.0400  |
| X3X4                    | -2.18                  | 76.13          | 1  | 76.13       | 50.54   | <0.0001 |
| Quadratic               |                        |                |    |             |         |         |
| X1²                     | 1.26                   | 43.27          | 1  | 43.27       | 28.73   | <0.0001 |
| X2²                     | 0.3685                 | 3.73           | 1  | 3.73        | 2.47    | 0.1366  |
| X3²                     | -0.2627                | 1.89           | 1  | 1.89        | 1.26    | 0.2799  |
| X4²                     | -0.8065                | 17.84          | 1  | 17.84       | 11.84   | 0.0036  |
| Residual                | 22.59                  | 15             |    | 1.51        |         |         |
| Lack of Fit             | 18.65                  | 10             |    | 1.86        | 2.36    | 0.1776  |
| Pure Error              | 3.95                   | 5              |    | 0.7895      |         |         |
| Cor Total               | 435.89                 | 29             |    |             |         |         |

\( R^2 = 0.9482, \text{ Adjusted } R^2 = 0.8998, \text{ Predicted } R^2 = 0.7406, \text{ CV} = 1.39\% \)
Fig. 3 Surface plot of interaction effect of the process parameters.
teraction terms \((X_1X_3)\) is significant as also seen on the surface plot (Fig. 3b), but the significant impact of the reaction time is less than the methanol/oil molar ratio. SBOME yield was observed to increase with increasing time. This is because enough time is required for the reaction to reach equilibrium, which favours the yield. Influence of time on biodiesel yield has also been shown in other studies\(^{10}\). The range of time (40-80 mins) selected was adequate for all the conversion processes conducted in this study.

Figure 3c depicts the combined interaction of temperature and methanol/oil molar ratio on SBOME yield. In transesterification, reaction temperature obviously influenced the rate of reaction and yield depending on the type of oil used. Increase in SBOME yield was observed to occur at low temperature and decrease in methanol/oil molar ratio. The \(p\)-value in Table 5 shows that the impact of temperature is more pronounced on the yield than methanol/oil molar ratio, although their interactive terms \((X_2X_4)\) is also significant. Decrease on SBOME yield was observed when the temperature is high and with high level methanol/oil ratio. Temperature range \((50 – 70^\circ C)\) was investigated for the transesterification of SBSO and all was sufficient for the conversion process in the studied range.

Figure 3d displays the influence of catalyst amount and time on SBOME yield. Catalysts are very important factor in transesterification as they speed up the rate of the reaction. The surface plot in Fig. 3 and Table 5, shows that the interactive terms of catalyst loading and time \((X_1X_3)\) had a significant effect on SBOME yield but the influence of catalyst loading is more obvious than that of time. For successful completion of the reaction, sufficient time is required in order to promote the dispersion of methanol in the reaction medium\(^{10}\). In this study, the best SBOME yield was observed at low catalyst loading. The plot also shows that increase in catalyst loading beyond 3 wt% leads to a decrease in SBOME yield. This might be due to the saturation of catalyst particles as concentration increases\(^{10}\). SBOME yield was found increasing with the low loading levels of the CMAPA and decreases with the high loading levels. The range of catalyst loading was selected from 1 – 5 wt% and this was actively adequate to speed up the rate of all the conversion reaction of SBSO in the range studied.

The interaction of catalyst loading, and temperature is shown in Fig. 3e. The surface plot and Table 5 revealed that both terms have significant impact on SBOME. But the effect of temperature is more obvious than catalyst loading on the yield. The significant effect of interaction of reaction time and temperature is displayed in Fig. 3f. The surface plot illustrates that both terms have a strong impact on SBOME yield. A higher SBOME yield was observed at low temperature and shorter reaction time.

### 3.6 SBOME synthesis modelling by ANN

SBOME yield prediction was obtained by ANN with Levenberg-Marquardt feedforward backpropagation algorithm, comprising of an input layer with four input process parameters (which include; methanol-to-oil molar ratio, catalyst loading, reaction time and reaction temperature) and an output layer with one output variable (SBOME). The selection of the best combination of transfer function was obtained by studying three transfer functions (tansig, purelin and logsig) for the output layer while maintaining for all training sets a constant hyperbolic tangent transfer (tansig) function for the hidden layer. The number of hidden neurons were also investigated from 5 to 15 and each of the neurons were trained with several number of iterations. Table 6 shows the network comparison with different transfer functions of Levenberg-Marquardt backpropagation with varied number of neurons in the hidden layer.

| ANN structure | Transfer function | \(R\)  | \(R^2\)  | RMSE   |
|---------------|-------------------|--------|----------|--------|
| Input:neuron:output |                    |        |          |        |
| 4:5:1         | Tansig            | 0.9435 | 0.8902   | 0.4681 |
|               | Tansig            | 0.8416 | 0.7083   | 0.5167 |
|               | Tansig            | 0.6545 | 0.4284   | 0.7741 |
| 4:10:1        | Tansig            | 0.9737 | 0.9480   | 0.5183 |
|               | Tansig            | 0.9923 | 0.9846   | 0.1034 |
|               | Tansig            | 0.7236 | 0.5236   | 0.8481 |
| 4:15:1        | Tansig            | 0.8887 | 0.7897   | 0.7275 |
|               | Tansig            | 0.9685 | 0.9379   | 0.3606 |
|               | Tansig            | 0.8213 | 0.6745   | 0.9147 |

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\(A. O. Etim, P. Musonge, and A. C. E.-Eboka\)

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layer. Nine pairs of transfer function combinations were examined for the hidden and output layers respectively, and the result is shown in Table 6. The best combination was selected based on the lowest and highest value obtained for RMSE (0.1034) and R (0.9923). Thus, the optimal combination of tansig-purelin transfer function with 10 neurons was used to develop the ANN model. Figure 4a shows the optimal ANN framework design developed for the prediction of SBOME yield with a topology of 4-10-1, which implies 4 process input variables in the input layer, 10 neurons for the hidden layer and 1 output layer which is the SBOME yield. The correspondence plot of correlation coefficient for training, testing, validation and all data sets are illustrated in Fig. 4b. The high values of R in the figure indicates a good correlation between the actual and the predicted values. High R values for the validation and testing sets also show a good predicting potential of the developed ANN model. ANN prediction of SBOME yield is
displayed in Table 2, under the same optimal condition predicted by the RSM model; methanol-to-oil ratio of 6:1, catalyst loading of 2.0 wt%, reaction time of 50 min and temperature of 55°C. ANN model predicted the optimum yield value of 96.45 wt%.

3.7 RSM and ANN predictive capacity and comparison

The predictive capabilities of RSM and ANN were assessed and compared based on statistical parameters which include R, R², RMSE, SEP, MAE and AAD. The results obtained are presented in Table 7. It can be seen that both models are effective in the prediction of SBOME yield. ANN model has higher values of R (0.99225) and R² (0.98456) compared to R (0.97375) and R² (0.94820) obtained respectively by the RSM model. The error analysis was also performed using RMSE, SEP, MAE and AAD, the lower values of these parameter signifies the good performance of the models. The level of accuracy and precision of the two models were evaluated by the values obtained from the statistical indices evaluated using Equations (4 - 12). The error values obtained by ANN model are lower than RSM model. Results generated for all the statistical indicators in Table 7 also shows that both models are effective but in terms of accuracy, ANN model performed better than the RSM model. The close alignment of the actual values and the predicted values illustrated in Fig. 5a, are also in support of the statistical results. The plot alignment

| Parameters | RSM          | ANN          |
|------------|--------------|--------------|
| R          | 0.97375      | 0.99225      |
| R²         | 0.94820      | 0.98456      |
| RMSE       | 0.18622      | 0.10337      |
| SEP (%)    | 0.21020      | 0.11673      |
| MAE        | 0.03470      | 0.01833      |
| AAD (%)    | 0.12643      | 0.07143      |

Table 7  Predictive evaluation of RSM and ANN models.

Fig. 5a  Plot of actual and predicted value for RSM and ANN.

Fig. 5b  The plot of experimental runs vs SBOME of actual and predicted yields.
of experimental runs with the SBOME of actual and predicted is also illustrated in Fig. 5b. The figures show that predicted values from ANN model are well aligned with the actual values than those of RSM. Similar observations have been reported by in modelling of waste cooking oil methyl ester using ANN and RSM, Esonye et al. (2019) in the optimization of biodiesel from Prunus amygdalus seed oil.

4 Conclusion

This study mainly investigated the feasibility and the optimization of biodiesel production from Marula (Sclerocarya birrea) seed oil through modelling and optimization of the transesterification process parameters by RSM and ANN. The RSM based on CCD was used to generate 30 experimental conditions using four factor five level CCD design. The predictive efficacy of the two models was assessed and compared by several statistical constraints such as R, R², RMSE, SEP, MAE and AAD. Result obtained shows that both models are efficient in their predictive capabilities, but the ANN model is confirmed to be accurate and more precise than RSM model. Transesterification was heterogeneously catalysed by calcined Musa acuminata peels ash (CMAPA). Optimal conditions predicted by the RSM for the transesterification of SBSO was methanol/oil molar ratio of 6:1, catalyst loading of 2 wt% reaction time of 50 min and reaction temperature of 55°C with actual SBOME yield of 96.45%. RSM model predicted the optimum yield of 96.65% while the ANN model predicted optimum yield of 96.45% under the same condition. Statistical evaluation of the developed model shows that ANN [(R = 0.99), (MAE = 0.01), (AAD = 0.07%), (SEP = 0.11%)] is superior to RSM model[(R² = 0.948), (MAE = 0.03), (AAD = 0.12%), (SEP = 0.21%)]. Optimization outcome showed that ANN prediction is favoured under the stated variable conditions. Fuel properties of SBOME produced were within the European (DIN EN 14214), SANS 833 and American (ASTM D6751) standard specifications. Therefore, it can be concluded that the oil from Marula seed is a potential feedstock source for biodiesel synthesis and its properties suggest that it is an excellent source of alternative biofuel for various engine applications.

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