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Softcomputing Model and Optimization of Soursop *(Annona muricata)* Seed Pyrolysis in a Fixed Bed Reactor

Chijioke Boniface Ugwuodo[1], Henry Ukochukwu Itiri[2], Iheonu Nduka Emmanuel[3], Kelechi Noble Akataobi[4], Ngozi Benedict Sunday[5]

[1,2,4,5]*Department of Chemical Engineering, Michael Okpara University of Agriculture, Umudike.*
[3]*Department of Chemical Engineering, Nazarbayev University, Astana, Kazakstan.*

Corresponding author: chijiokeugwuodo@mouau.edu.ng (Ugwuodo C.B)

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Abstract

The introduction of machine learning in predicting yield for the pyrolysis process stimulates the wide usage of first-generation biomass, especially in producing bio-oil and biochar. This study focused on soft computing optimization of soursop seed pyrolysis using ANN and ANFIS. Soursop (*Annona muricata*) seeds, often discarded as agricultural waste, contain valuable organic components suitable for thermochemical conversion. This study explores the pyrolysis of soursop seeds in a fixed-bed reactor. It models the process using soft computing techniques, Artificial Neural Networks (ANN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to optimize bio-oil yield. Samples of the soursop seed were washed, oven-dried, and ground the soursop seed using a mill, screening it to various particle sizes before valorizing it. Seventeen (17) pyrolysis experiments were conducted using varying temperatures, particle sizes, and inert gas flow rates. The resulting bio-oil yields were used to train both ANN and ANFIS models. Model performance was evaluated using statistical metrics such as mean square error (MSE) and coefficient of determination (R^2). ANFIS achieved superior predictive accuracy (R^2 = 0.999, MSE = 0.0005) compared to ANN (R^2 = 0.997, MSE = 0.7235), confirming its effectiveness in modeling the pyrolysis process. Optimal conditions for bio-oil yield (27.8%) were identified at 500°C, 3.5 mm particle size, and 1.25 L/min inert gas flow rate. Physicochemical characterization of the bio-oil revealed favorable fuel properties, including a high heating value (41.5 MJ/kg), acceptable viscosity, flash point (195.8°C), and pour point (−25°C). GC-MS and FTIR analyses further confirmed the presence of essential fatty acids and functional groups consistent with fuel-grade bio-oils. This study demonstrates that soft computing models, particularly ANFIS, are effective tools for optimizing bio-oil production from biomass such as soursop seeds. The findings support the valorization of agricultural waste as a viable pathway for sustainable energy production and provide a framework for scaling bio-oil production processes in bioenergy industries.

Keywords: Artificial neural networks; adaptive neuro-fuzzy inference systems; optimization; pyrolysis; soursop seed

1. Introduction

Fears for the environment over greenhouse gas (GHG) emissions and oil shortages caused more research into a clean, renewable, and sustainable energy source that will play a big part in the future energy supply (Efetobor *et al*., 2023).These renewable energy sources are considered crucial possibilities for energy supply, addressing global energy demand, climate change, and energy security (Onokwai *et al*., 2022a). Despite the rising acknowledgment of renewable energy, its average contribution to global energy reserves remains constrained (Fahmy *et al*., 2020; Nnodim *et al*., 2022). Challenges and uncertainties emerge from diverse ways of transforming renewable energy into fuels (Dhanavath *et al*., 2019). These methods encompass solar, hydro, wind, and biomass; waste and virgin biomass benefit from their non-zero carbon footprint and ample availability (Kumar *et al*., 2019).

Biomass is acknowledged as a sustainable, environmentally favourable renewable resource for bioenergy generation and is widely accessible worldwide (Onokwai *et al*., 2022c). The utilization of biomass is garnering considerable interest in conventional energy sectors due to the rising global energy demand and environmental concerns. It is intricate and has a minor proportion of ash, nitrogen, and sulphur. Consequently, the combustion of biofuels produces reduced levels of deleterious gas pollutants such as soot, sulphur dioxide (SO_2), and nitrogen oxides (NO_x). CO2 emissions generated during bio-oil production may be repurposed for plant use (Onokwai *et al*., 2022a).

Many countries possess substantial biomass that can be utilized as energy resources. Different categories of biomass resources, including sludge from wastewater treatment facilities, municipal solid waste, forestry residues such as bark, sawdust, and wood chips, as well as agricultural by-products like wheat straw, rice husk, and palm kernel shell, are widely accessible and possess a relatively high energy content (Go *et al*., 2019). Within the context of agricultural residues, the soursop seed signifies a notable potential for advancing the bioenergy sector (Demirbas *et al*., 2006).

Soursop (*Annona muricata*) is a tropical fruit celebrated for its nutritional and medicinal properties. Yet, its seeds are often overlooked and discarded as agricultural waste (Martínez *et al*., 2020). These seeds, which comprise about 20% of the fruit's total weight, contain valuable organic material that can be converted into useful products through pyrolysis (Ishaq *et al*., 2020). Soursop seeds contain lipids, proteins, carbohydrates, and essential minerals. A study by Pinto *et al*. (2021) reported that soursop seeds contain approximately 20.5% fat, 47.0% carbohydrates, 2.4% protein, and 8.5% moisture. Converting this waste into bio-oil via a thermochemical process offers enhanced efficacy and advantages for substituting fossil fuels. Consequently, numerous researchers have investigated its energy potential, yielding promising results (Onokwai *et al*., 2022b). Biomass conversion to bio-oil entails thermochemical conversion processes (Balogun *et al*., 2019). Thermochemical conversion involves biomass breakdown at temperatures exceeding 150 °C underregulated oxidation or heating conditions to produce bio-oil, bio-char, and syngas (Hassan *et al*., 2017). Chowdhury *et al*. (2017) report that thermochemical conversion processes encompass combustion, gasification, and pyrolysis. The gasification process is effective but entails significant investment costs, whereas combustion is the most prevalent and straightforward conversion method; nonetheless, it presents various environmental risks (Sahoo *et al*., 2021). The pyrolysis method provides a cost-effective and straightforward process for decomposing biomass into biofuels without oxygen (Gautam and Chaurasia, 2020). The classification of pyrolysis is contingent upon the heating rate, categorizing it into slow, fast, and flash pyrolysis (Guedes *et al*., 2018). Fast pyrolysis demonstrates greater efficiency in generating substantial quantities of bio-oil within the temperature range of 300–700 °C and heating rates of 10–200°C/s (Onokwai *et al*., 2023a).

Pyrolysis operating parameters, such as inert gas flow and temperature, have been examined for their impact on bio-oil yield. Therefore, investigating optimal operating conditions to maximize yield is essential. This concern has garnered significant attention from researchers (Park *et al*., 2019). In search of optimal bioprocessing conditions, researchers are exploring modeling, predicting, and optimizing process parameters using Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Dadhania *et al*., 2021; Ingie *et al*., 2023; Nwosu-Obieogu *et al*., 2024). RSM evaluates linear, interaction, and quadratic effects to identify ideal operating conditions for processes (Marzouk *et al*., 2021; Samuel *et al*., 2020; Ude *et al*., 2020; Fakhari, 2023). While RSM has been used for the pyrolysis of seeds for bio-oil, it has limitations, such as the inadequacy of models for extrapolation beyond experimental ranges and its struggles with complex variables. ANN and ANFIS, on the other hand, are better at making predictions instead (Okeleye and Betiku, 2019; Samuel *et al*., 2022; Belmajdoub and Abderaft, 2023). ANN is a powerful tool for pattern recognition and regression analysis, capable of learning from vast datasets to identify underlying trends. However, it can sometimes act as a "black box," lacking transparency in how it derives outputs. However, ANFIS combines the learning abilities of neural networks with the human-like reasoning of fuzzy logic, which makes it easier to understand and more adaptable (Ude *et al*., 2020; Nwosu-Obieogu *et al*., 2024). By using both models, researchers can take advantage of ANN's speed in processing data and ANFIS's ability to improve interpretability and adaptability. This lets them come to stronger and more insightful conclusions in areas with many variables. Information on the pyrolysis of soursop seed for bio-oil through ANN and ANFIS remains limited. Therefore, this study aims to utilize soft computing techniques to model the pyrolysis of soursop seeds for bio-oil yield.

2. Materials and Methods

2.1 Materials

The soursop seeds were gathered from a soursop fruit plantation in Uturu, Nigeria. The soursop seeds were collected and purified to eliminate soil, stones, and other extraneous substances that could disrupt the pyrolysis process. The soursop seed was oven-dried (VO-25) for 48 hours at a controlled temperature (60-70 °C) until a constant weight was achieved to determine the initial moisture content. The ground sample was sieved to uniform particle size in the 1-3mm range and preserved in an air-tight container for further analysis.

2.2 Pyrolysis Procedures

The pyrolysis of soursop seed was carried out in a lab-scale fixed-bed pyrolyzer(locally fabricated). Dried soursop seeds of varying particle sizes were introduced into the reactor for pyrolysis. The reactor was sealed with a lid and steam gasket to ensure gas impermeability. Nitrogen gas was purged downstream of the tubular reactor at a flow rate of 1.5 L/min to establish an inert atmosphere. The heaters were heated to 500 °C by adjusting the electrical control panel. A thermocouple was positioned at the reactor's apex to gauge the internal temperature. The reactor's temperature was periodically checked with a thermocouple as a safety measure. The volatile products created in the reactor were purged downward and flowed into the condenser. The condensation apparatus was established by immersing the filtering flask in cold water. The liquid oil and solid char were recovered separately, while non-condensable gas was vented into the atmosphere. The technique was repeated according to the number of runs specified in the experimental design. The bio-oil and char were weighed using a digital scale, recorded, and securely stored in separate, well-sealed containers at room temperature. The yield percentage of pyrolysis products was calculated using Equation 1.

$$\%\ Yield\ of\ Product = \frac{mass\ of\ product}{mass\ of\ feedstock} \tag{1}$$

2.3 Soft Computing of the Oil Extraction

The pyrolysis of soursop seed for bio-oil was modeled with artificial neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) using a design matrix generated by Design Expert version 13. The dependent variable is oil yield, while the independent variables are temperature, particle size diameter, andinert gas flow rate,with 17 experimental runs,as shown in Table 1.

2.3.1 ANN Modeling

The multi-variable-single output (MISO) neural architecture (Figure 1) was implemented to model the pyrolysis process. The independent variables are listed in Table 1, while the single output represents the bio-oil yield. The dataset in Table 1 was duplicated, and the number of neurons was adjusted to prevent overtraining and overfitting. Consequently, thirty-four (34) sets of data were utilized for training, and the data was analyzed using the logsig nonlinear transfer function in the hidden layer and the purelin function in the output layer. As noted by Ude *et al*. (2022), the network was trained with seventy percent of the data, representing 24 samples, while fifteen percent was allocated for testing and validation, each comprising five (5) samples. The model's performances were assessed with mean square errors (MSE) and the coefficients of determination.

2.3.2 ANFIS Modeling

The ANFIS network designs employed five distinct layers, including the fuzzy process, output, rule, defuzzy process, and total addition layers (Ude *et al*., 2022). The first-order Sugeno model was applied for this study, using an input variable for oil yield (Figure 2). The fuzzy rules implemented were based on the IF-THEN rules developed by Takagi and Sugeno, as referenced by Betiku*et al*. (2018) and Ude *et al*. (2022). The modelling was conducted using the fuzzy logic toolbox in MATLAB R2013a.

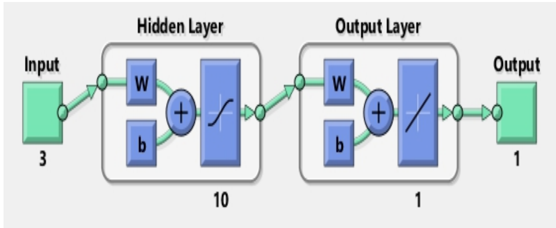

Figure 1: MISO neural architecture

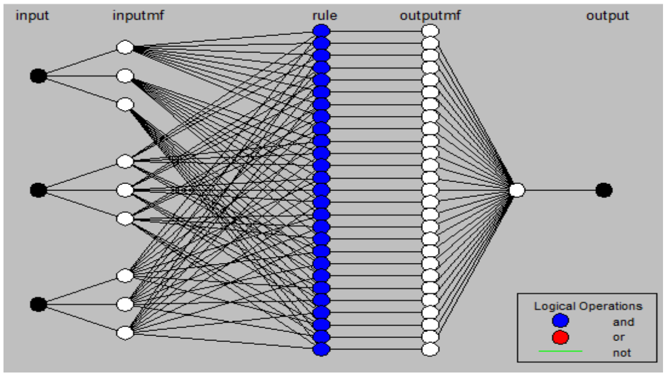

Figure 2: ANFIS architecture for modeling Oil extraction.

2.3.3 Statistical Evaluation of the Models

The performance of each model was validated by assessing statistical metrics, including root-mean-square error (RMSE), coefficients of determination (R^2), and coefficients of regression (R). The statistical indicators were evaluated using Equation 2-4,as Ude et al. (2022) outlined.

$$RMSE = \sqrt{\tfrac{1}{n}\textstyle\sum_{i=1}^{n}(\,w_{a,i} - w_{p,i}\,)^2} \tag{2}$$

$$R = \frac{\sum_{i=1}^{n}(w_{p,i} - w_{p,ave}).(w_{a,i} - w_{a,ave})}{\sqrt{[\sum_{i=1}^{n}(w_{p,i} - w_{p,ave})^2]\ \ [\sum_{i=1}^{n}(w_{a,i} - w_{a,ave})^2]}} \tag{3}$$

$$R^2 = \frac{\sum_{i=1}^{n}(w_{a,i} - w_{a,ave})^2}{\sqrt{\sum_{i=1}^{n}(w_{p,i} - w_{p,ave})^2}} \tag{4}$$

2.4 Bio-oil Characterization

The produced bio-oil was subjected to FTIR, GCMS, and physiochemical analysis to identify the functional group and fatty acid profile of the bio-oil, as well as the physicochemical properties of the bio-oil. This was carried out according to the standards set by the American Society for Testing Materials (ASTM, 2014).

3. Results and Discussion

3.1 ANN Modelling of Soursop Seed Pyrolysis

The artificial neural network (ANN) was utilized to forecast the pyrolysis parameters, employing a supervised learning approach. Figure 3 illustrates the network's training performance, revealing a mean square error of 0.7235 for predicting bio-oil yield at a maximum epoch of 5, indicating commendable performance with minimal errors. Figure 4 shows the MISO network model's error histogram, which shows that the errors were within the range of −0.1694 to

Table 1: Response of Experimental Design Matrix

	Factor 1	Factor 2	Factor 3	Response 1	ANN Predicted	ANFIS Predicted
Run	A:Temperature (ºC)	B:Particle size (mm)	C:Inert gas flow (L/min)	Oil yield (%)	Oil Yield (%)	Oil Yield (%)
1	500	6	1	33.1	33.09	33.10
2	600	4	1	30	30.38	30.00
3	600	4	1.5	20.9	20.85	20.90
4	500	4	1.25	27.4	27.55	27.40
5	500	1	1.5	21	20.97	21.00
6	500	4	1.25	27.4	27.55	27.40
7	500	1	1	37	37.02	37.00
8	500	4	1.25	27.4	27.55	27.40
9	400	4	1.5	16.25	14.40	16.25
10	400	6	1.25	22.3	22.41	22.29
11	500	6	1.5	30.9	31.36	30.90
12	600	1	1.25	27.8	27.76	27.80
13	500	4	1.25	27.4	27.55	27.40
14	400	4	1	25.9	26.20	25.90
15	600	6	1.25	22	22.13	22.00
16	500	4	1.25	27.4	27.55	27.40
17	400	1	1.25	17.2	17.28	17.20

0.06158 (zero region), indicating good performance. This compared well with Anas *et al*. (2024). Additionally, Figure 5 presents the model's plot for bio-oil yield prediction, demonstrating a strong correlation between the predicted and actual yields. The correlation coefficient was 0.9971, suggesting that the model effectively predicted the oil yield. This is in line with the report of Umeagukwu*et al*. (2023) and Anas *et al*. (2024).

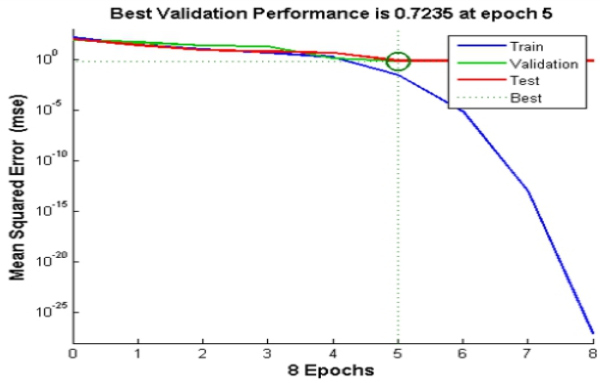

Figure 3: MISO Performance Error for predicting of Oil yield

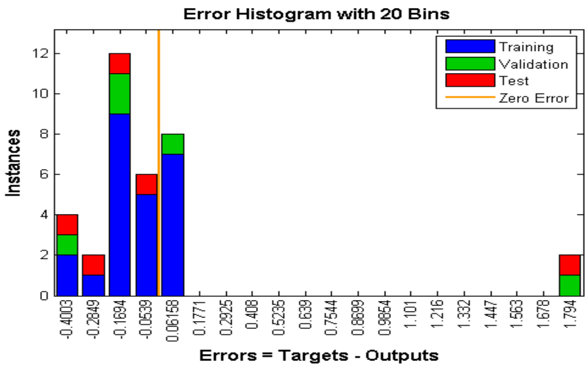

Figure 4: Histogram showing error distribution of experimented data and predicted data on MISO mode

3.2 ANFIS Modelling

The responses from the experimental design matrix for pyrolysis of soursop seed for bio-oil were modeled using the ANFIS approach, as shown in Table 1. Figure 6 illustrates the correlation between the actual and generated yields for the ANFIS pyrolysis model. The model achieved an R^2 of 0.999, with an error of 0.00050095, as demonstrated in Figure 6. The high R^2 value and the low average testing error indicate a strong correlation between the actual and generated results, with the model accounting for 99.99% of the variability observed. The results align with the previous research conducted by Nwosu-Obieogu *et al*. (2021) regarding antioxidant yields from luffa oil, Yue *et al*. (2018) on modeling biodiesel production from castor using ANFIS, and Roy *et al*. (2019) in the ANFIS prediction of the almond seed oil extraction process.

Also, surface plots were made to see how different combinations of pyrolysis factors affected the bio-oil yield. These can be seen in Figure 7 (a–c). Specifically, Figure 7a illustrates the interactive influence of the temperature (°C) and particle size diameter (mm) on the bio-oil yield of soursop seed pyrolysis. It is evident that as both the temperature and particle size diameter rose, the bio-oil yield decreased, then started to increase after 500 °C and 4 mm. The initial drop in the amount of bio-oil may be due to the secondary cracking of the oil vapor, thereby producing more gas over extended exposure to high temperatures.

Figure 7b illustrates how temperature and inert gas flow rate interact to influence soursop seed pyrolysis bio-oil yield. The figure indicates that while increasing temperature and inert gas flow rate reduce bio-oil yield, yields rise when the temperature exceeds 500°C. The inert gas flow rate surpasses 1.2 L/min. This increase in yield at elevated temperatures and gas flow rate could be linked to the complete devolution of the material and fast purging of the vapor oil into the condenser by the inert gas.

Figure 7c depicts the combination of particle size diameter and inert gas flow rate on bio-oil yield. It is evident from the plot that bio-oil yield decreases with rising particle size diameter and inert gas flow rate. However, yield increases after 4 mm and 1.2 L/min of the particle size and gas flow rate, respectively. This improvement can be due to the greater quantity of oil in the raw material and the quick purging of the vapor gas into the condenser for condensation.

The optimization of bio-oil yield from the pyrolysis of soursop seeds was conducted through ANFIS rules, focusing on temperature, particle size, diameter, and inert gas flow rate. The findings indicated that an oil yield of 27.8% from soursop seed oil was achieved when these parameters were set to 500 °C, 3.5 mm, and 1.25 L/min. Furthermore, the validation of the optimal extraction results showed a percentage error of less than 1%. The model demonstrated a strong capability to accurately predict outcomes, confirming its effectiveness in achieving optimal results. These findings are consistent with those of Ojediran *et al.* (2020) on yam slice drying prediction using ANFIS.

3.3 Performance Evaluation of the developed Models

Statistical metrics were employed to assess the performance of the ANN and ANFIS models developed for predicting bio-oil yield from the pyrolysis of soursop seeds, with the results presented in Table 2. The R^2 values for the ANFIS model were slightly higher than those of the ANN model. Moreover, the ANFIS exhibited lower error rates than the ANN model, and both models displayed low calculated mean squared errors (MSEs). This suggests that while the ANFIS is more effective in predicting bio-oil yield from soursop seed through pyrolysis, with ANFIS predicting the yield at 99.9% and the ANN model at 99.3%, both models are viable options for estimating bio-oil yield.

Table 2: Statistical Indices of the Model

Index	ANN	ANFIS
R^2	0.997	0.999
MSE	0.7235	0.00050095

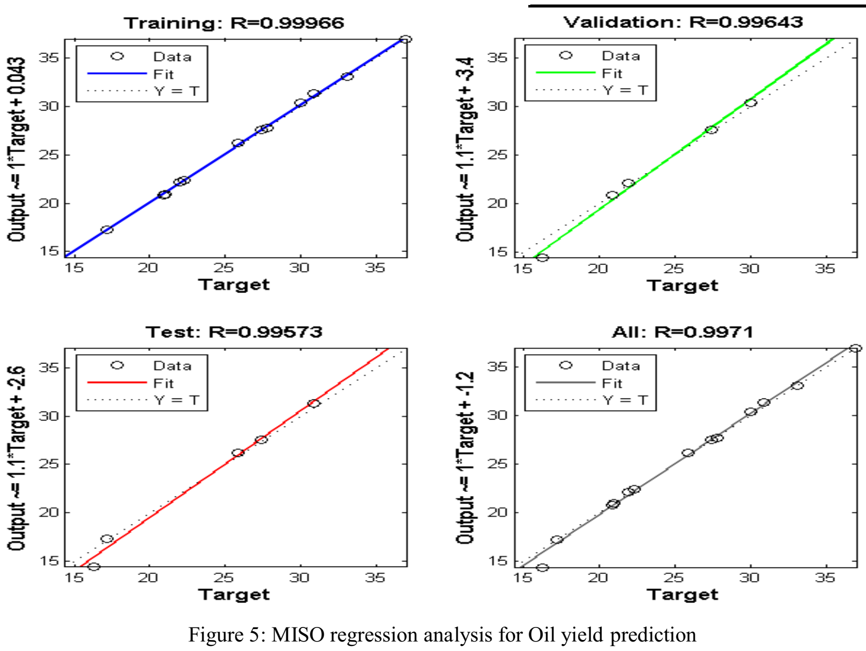

Figure 5: MISO regression analysis for Oil yield prediction

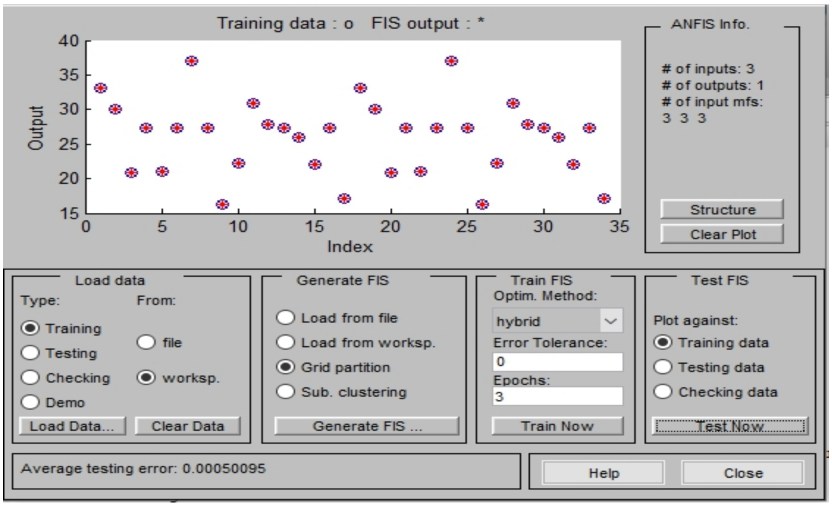

Figure 6: Experimental and predicted oil yield

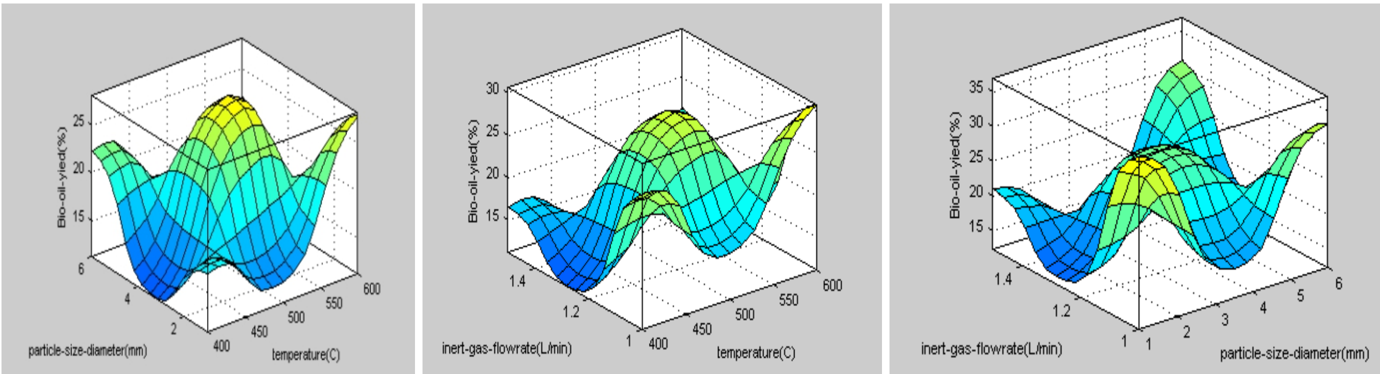

Figure 7: Surface Plots of the ANFIS model for the interaction ef fect of (a) temperature and particle size diameter, (b) temperature and inert gas flow rate, and (c) particle size diameter and inert gas flow rate.

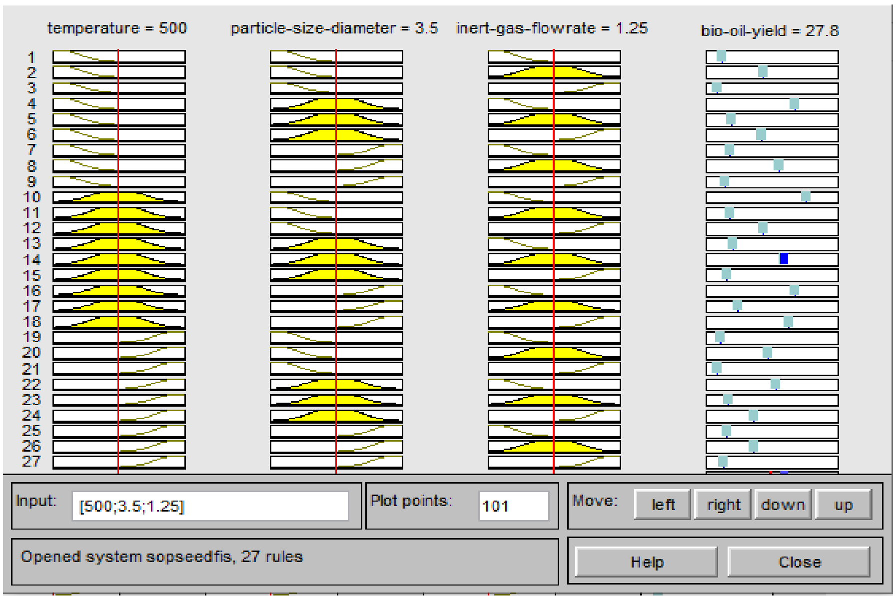

Figure 8: ANFIS rule viewer for soursop seed pyrolysis process for bio-oil yield.

3.4 Determination of the Bio-oil Properties

3.4.1 Physical and chemical properties of the Bio-oil

Table 3 depicts the physical and chemical characteristics of the bio-oil generated from the pyrolysis of soursop seeds. The moisture content in bio-oil originates from the original moisture in the biomass and results from processes during pyrolysis, including the dehydration of cellulose, hemicellulose, and lignin found in the biomass (Ren *et al*., 2016). The water in bio-oil presents both advantages and disadvantages; it reduces viscosity, facilitating a free-flowing liquid while simultaneously decreasing heating value and flame temperature, leading to ignition challenges. Bio-oil with elevated water content can be utilized in engines or boilers, but it requires certain modifications and conditions (Yang *et al*., 2015). According to bio-oil regulations and the ASTM D 7544 standard for fast pyrolysis oil (Grades D and G), the maximum allowable water content for fuel in turbines and boilers is 25-30% (Lehto *et al*., 2014). Solubilizing chemicals in bio-oil, including acids, alcohols, ketones, and aldehydes, complicates water separation from bio-oil (Yang *et al*., 2015). The pour point of the generated bio-oil was determined to be −25°C. The pour point of the bio-oil produced in this study complies with ASTM D7544-12 standards, which provide a maximum of ≤ -9. The transportation and storage of bio-oil at elevated temperatures can be mitigated by a greater flash point, reducing the risk of autoignition and fire dangersand enhancing the safety of its handling, shipping, and storage. The bio-oil produced in this study exhibited a flash point of 195.80°C, aligning well with standard bio-oil and commercial petroleum diesel (El Farissi *et al*., 2022). At 100 °C, the bio-oil generated exhibited a viscosity of 82.60 Pa·s. This range nearly satisfies the typical bio-oil standards. Consequently, bio-oil can be utilized in diesel engines directly or in conjunction with diesel fuel (Rajia *et al*., 2023). The viscosity is consistent with findings by Ogaga *et al*. (2017).

The bio-oil higher heating value (calorific value) was ascertained by combusting a measured sample in an oxygen-bomb calorimeter, Leco AC-350, under regulated conditions, yielding a 41.50 MJ/kg value. This is comparable to transportation-grade fuel but slightly inferior to petrol (47 MJ/kg) and diesel fuel (43 MJ/kg) (Rajia *et al*., 2023).

Table 3: Physic and chemical features of oil

Item	% value
Moisture Content	13. 10 ± 0.4
Pour Point °C	-25
Flash Point °C	195.80
Viscosity @100°C (Pa.s) ASTM- D44	82.6±1.60
Viscosity Index	165
HHV (mj/kg)	41.50

3.4.2 Gas chromatography and mass spectrometry (GC-MS) analysis for the bio-oil.

Figure 9 presents the bio-oil chemical composition achieved using GC-MS, and the concentration of these acids is presented in Table 4. The compositions of the pyrolytic bio-oil were assessed based on the relative peak area of identified elements derived from the chromatogram acquired from GC–MS analysis, which aligns with the findings of Laouge et al. (2020). The bio-oil has a total of eight peaks and is made up of Tetradecanoic Acid, Hexadecanoic Acid, Heptadecanoic Acid, 9- Octadecadienoic Acid, Octadecadienoic Acid, Eicosanoic Acid, Docosanoic Acid, and Heptacosanoic Acid. However, the most significant fatty acids in the bio-oil are 9, Octadecadienoic Acid (45.55%), Hexadecanoic Acid (27.80%), and Octadecadienoic Acid (24.30%), while Heptadecanoic Acid has the least concentration of 0.50%. Since linoleic is the predominant monounsaturated fatty acid and makes up 45.55% of the total fatty acid content, the oil belongs to the linoleic acid group (Sonntag, 2012). This result compared well with the report of (Okokpujie *et al*., 2023; Álvarez-Chávez *et al*., 2019; Ude *et al*., 2023).

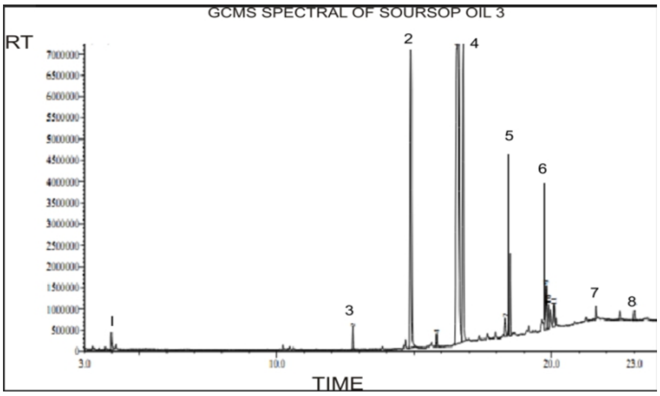

Figure 9: GC-MS of bio-oil compound produced from soursop seed.

Table 4: Fatty acid composition of Soursop seed oil

Retention Time	Fatty Acid Present	Compound Names	Molecular Formular	% Concentration
12.75	Tetradecanoic Acid	Myrisic Acid	$C_{14}H_{28}O_2$	0.90
14.88	Hexadecanoic Acid	Palmitic Acid	$C_{16}H_{32}O_2$	27.80
15.80	Heptadecanoic Acid	Margaric Acid	$C_{17}H_{34}O_2$	0.50
16.60	9, Octadecadienoic Acid	Linoleic Acid	$C_{18}H_{31}O_2$	45.55
16.80	Octadecadienoic Acid	Stearic Acid	$C_{18}H_{34}O_2$	24.30
18.80	Eicosanoic Acid	Arachidic Acid	$C_{20}H_{40}O_2$	12.60
20.10	Docosanoic Acid	Behenic Acid	$C_{22}H_{44}O_2$	1.05
21.60	Heptacosanoic Acid	Cosnic Acid	$C_{27}H_{54}O_2$	0.65

3.4.3 FTIR analysis result of the bio-oil

Table 5 depicts the FTIR spectrum of soursop seed oil. This research was undertaken to identify the different functional groups in the bio-oil. The investigation indicates the presence of =C-H functional groups (alkenes) at a precise frequency of 1450.2 cm⁻¹. All of them display double-bonded bending-type vibrations within the spectrum's low energy and frequency range. They are ascribed to functional groups comprised of unsaturated olefinic chemicals (alkenes). These substances could be components of the methyl esters from unsaturated fatty acids found in bio-oil. The peaks detected at 1050.2 cm⁻¹ are attributed to the stretching vibrations of the C-O and C-O-C molecules. The band observed at 1634.2 cm⁻¹ is associated with the bending vibrations of C=C bonds. In contrast, the band region at 1450.1 cm⁻¹ is associated with the bending vibrations of C-H methyl groups. An assortment of fragrant chemicals is identified within the wavelength range of 1626.3 cm⁻¹. The existence of the 2920.1 cm⁻¹ area indicates the presence of a carboxylic acid with an elongated O-H group. The peaks observed at 2968.1 cm⁻¹ indicate the symmetric stretching vibrations of the C-H alkane groups. Both methyl (CH_3) and methylene groups require substantial energy to generate stretching vibrations in their bonds. By contrast, alkene groups' usual C-H bending vibrations are detected at lower energy and frequency ranges. The peak observed at 3390.2 cm⁻¹ is ascribed to the stretching vibration of alkene groups with =C-H bonds. This result aligns with the report of Ishaq *et al*. (2020).

Table 5: Functional Groups Identified from FTIR Spectrum of Soursop Seed

Wavenumber (cm^{-1})	Functional Group	Type of Vibration	Possible Compounds
~3300-3400	O−H stretch	Strong, broad	Alcohols, phenols (lignin, cellulose)
~2920	C−H stretch	Medium	Alkanes (lipids, fatty acids)
~1730	C=O stretch	Strong	Esters, aldehydes, ketones (oils)
~1600-1650	C=C or aromatic C=O stretch	Medium	Aromatics, lignin
~1510	Aromatic ring stretch	Medium	Lignin derivatives
~1450	C−H bending	Medium	Alkanes, methyl groups
~1240-1270	C−O stretch	Medium	Esters, ethers, cellulose
~1020-1050	C−O−C or C−OH stretch	Strong	Polysaccharides (cellulose, hemicellulose)

4. Conclusion

The research focused on optimizing the pyrolysis of soursop seed for bio-oil through soft computing techniques, explicitly using Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The findings indicated that ANFIS outperformed ANN in predicting bio-oil yield, demonstrating the highest coefficient of determination and the lowest error rates. An optimal bio-oil yield of 27.8% was achieved by adjusting the parameters to 500°C, 3.5 mm, and 1.25 L/min for temperature, particle size diameter, and inert gas flow rate, respectively. This predictive model for pyrolysis of soursop seeds is expected to promote the broader use of agricultural waste for bio-oil production. Ultimately, this research represents a significant advancement in developing sustainable and renewable energy sources, which could benefit environmental health and local economies.

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