Global NEST Journal, Vol 27, No X, pp 1-8

Statistical optimization of biodiesel production from the non-edible seed of *mimusops elengi* using RSM and ANN studies

Suresh Kumar A[1] and Ranjitha J[2*]

[1]Department of Thermal and Energy Engineering, School of Mechanical Engineering, Vellore Institute of Technology, Vellore-632014, Vellore, India

[2]CO_2 Research and Green Technologies Centre, Vellore Institute of Technology, Vellore-632014, Vellore, India

Received: 12/12/2024, Accepted: 20/01/2025, Available online: 10/02/2025

*to whom all correspondence should be addressed: e-mail: ranjitha.j@vit.ac.in

https://doi.org/10.30955/gnj.007143

Graphical abstract

Abstract

The present paper mainly focused on the statistical optimization of biodiesel production from the non-edible seeds of *Mimusops Elengi* using a KOH base-catalyzed Transesterification process. Consequently, it compares the prediction and simulating efficiencies of the Response Surface Method (RSM) and Artificial Neural Network (ANN) for biodiesel yield achieved *via* the Transesterification process. This experimental reaction analyzed various process variables influencing the transesterification process: methanol oil ratio, catalyst concentration, reaction temperature, and time. In both statistical analyses, RSM and ANN studies obtained R^2 values of 0.9923 and 0.9992, respectively. The optimum biodiesel yield achieved was 89% at a 1:7.5 molar ratio of methanol and *M. Elengi* seed oil using potassium hydroxide as a base catalyst.

Keywords: Biodiesel, non-edible, *mimusops elengi l,* response surface methodology, artificial neural network

1. Introduction

Energy demand is increasing day by day due to the increase in the human population all over the world (Panwar, Kaushik, and Kothari 2011) In the past decade, the cost of petroleum crude oil has increased in the international market, and fossil fuel exhaustion and limitations resulted in alternative, renewable, and sustainable sources (Stigka, Paravantis, and Mihalakakou 2014; Yusuf, Kamarudin, and Yaakub 2011). Hence, alternative fuels are required to sustainably satisfy the world's energy needs. Biodiesel, known as Fatty Acid Methyl Ester (FAME), is an eco-friendly and renewable fuel that can be used as an alternative to diesel fuel independently (or) blended with diesel (Jamil *et al*. 2021). Biodiesel derived from various feedstocks, like waste fats, waste cooking oils, and non-edible seeds, is used as a feedstock for biodiesel production (Athar and Zaidi 2020; Hamza *et al*. 2021). Several research studies have been carried out in the production of biodiesel from various non-edible seeds like *Bryonia Dioica (Sanyasi kai), Garcinia xanthochymus (Jaarige), Mimusops elengi (Ranja), Terminalia bellirica (Shanthi kai) and Anamirta Cocculus (Chiplotte)* (Ala'a H. Al-Muhtaseb *et al*. 2020; Habib *et al*. 2020; Jume *et al*. 2020). The biodiesel produced from various non-edible seeds is tested in a diesel engine. Consequently, multiple processes produce biodiesel, such as transesterification, pyrolysis, micro-emulsion, and dilution (Esan, Adeyemi, and Ganesan 2020), and transesterification is the most viable and economical process for biodiesel production. The transesterification process is the chemical reaction between the triglycerides (or) vegetable oils and the alcohol in the presence of a catalyst to produce biodiesel (Hájek *et al*. 2017; Kirubakaran and Arul Mozhi Selvan 2018; Vonortas and Papayannakos 2014) A base-catalyzed transesterification of radish seed oil (33.5%) with Methanol, Ethanol, and Mixed Methanol-Ethanol resulted in alkyl esters (biodiesel). The blends of the produced biodiesel are tested in a diesel engine and compared with the ASTM D6751 standard (Adama and Anani, 2023; Vávra, Hájek, and Skopal 2017). Similarly, a two-step transesterification process was performed for *Argemone Mexicana* seed oil and optimized biodiesel reaction and analyzed its performance characteristics in the CI engine (Kumar Paswan *et al*. 2023; Naveenkumar and Baskar 2020). Among the various non-edible seed feedstocks, *Mimusops Elengi* is available in most parts of India, and the biodiesel production from this plant is not well established; only

limited research works are available (Ala'a H. Al-Muhtaseb 2021; Potrč *et al*. 2021) Recently, biodiesel was produced from the seed oil of *M. elengi* using a potassium aluminum silicate, and the biodiesel yield was achieved up to 73.4% (Rezania *et al*. 2019; Sierchuła *et al*. 2019). Response Surface Methodology (RSM) and Artificial Neural Network (ANN) are used to determine optimal biodiesel production yield efficiency. The prediction capabilities of RSM and ANN are evaluated and compared using root mean square error to view the two approaches better (Chutia *et al*. 2023; Kesharvani *et al*. 2024). Generally, mathematical modeling and statistical optimization of the biodiesel yield are performed based on process parameters, mainly molar ratios, catalyst concentration, Reaction time, and temperature (Al-dobouni, Fadhil, and Saeed 2016; Rao *et al*. 2012). Response surface methodology (RSM) is one of the multivariate methods used to analyze reaction parameters and quantitative test factors (Anjum, Prakash, and Pal 2019; Kumar, Varun, and Chauhan 2013). ANN is based on organic sensory systems and nonlinear issues and has a solid learning capacity to anticipate (Garg and Jain 2020; Krupakaran, Hariprasad, and Gopalakrishna 2018). These approaches are being utilized in various fields for statistical understanding of process variables and optimization of yield efficiency (Fadhil, Sedeeq, and Al-Layla 2019; Sangeetha *et al*. 2023; Malani *et al*. 2017). The relationship between simulation and experimental data has revealed a significant reaction parameter optimisation for the enhancement of biodiesel yield (Choudhury, Chakma, and Moholkar 2014). This paper focuses on the statistical optimization of biodiesel production from the seed oil of *Mimusops Elengi* using RSM and ANN.

2. Methodology

2.1. Material and methods

All the chemicals, including n-hexane, isopropanol, Potassium Hydroxide (KOH), and Methanol (CH_3OH), were purchased from Sigma-Aldrich (India) and SD Fine Chemicals (India).

2.2. Collection of seeds

The *Mimusops Elengi* seeds were collected from Vellore Institute of Technology (VIT) Nursey Garden, Vellore, Tamil Nadu, India. The external shells of the seeds were removed, and the inner part was known as the kernel. The seed kernels were cleaned using distilled water to remove the suspended particles and impurities. The cleaned seeds were dried in a hot air oven for five hours at 40-50°C, and the moisture content was removed. Finally, the seeds were crushed, and a powder was obtained and utilized to extract bio-oil from the *Mimusops Elengi* seeds.

2.3. Significance of mimusops elengi seeds

Mimusops elengi, also known as maulsari, is not utilized for biodiesel production. Compared to other non-edible seeds like Jatropha curcas, Pongamaia Pinnata, Hevea brasiliensis, Azadirachta indica, Madhuca indica, Sapindus mukorossi, Mimusops elengi contains similar oil content seeds have not been thoroughly investigated. Biodiesel production requires oils containing high amounts of unsaturated fatty acids, such as oleic acid, linoleic acid, and palmitic acid. According to the previous research report (Gami, Pathak, and Parabia 2012). M. elengi seed oils contain various fatty acids like capric, lauric, myristic, palmitic, stearic, oleic, and linoleic acids suitable for biodiesel production.

2.4. Sustainability

Mimusops elengi has been a hardy, fast-growing tree throughout time, and its cultivation could potentially have environmental benefits, such as soil stabilization and carbon sequestration. However, its overall potential for large-scale biodiesel production satisfies the oil yield, extraction feasibility, and costs compared to other feedstocks. It is an economically viable biodiesel feedstock compared to other feedstocks like *Jatropha curcas*, *Pongamaia Pinnata*, *Hevea brasiliensis, Azadirachta indica, Madhuca indica, Sapindus mukorossi, Mimusops elengi* used for biodiesel production. TEA (Techno-economic analysis) is mainly based on seed harvesting, crude oil extraction, biodiesel production, catalyst synthesis, and engine testing.

2.5. Biooil extraction and transesterification

The bio-oil was extracted from the kernel of the *mimusops elengi* seeds using the Soxhlet extraction method. In this method, the seeds were coarse powdered and packed in the thimble for Soxhlet extraction. Initially, 300g of a dried kernel of the *mimusops elengi* seeds powder was taken in a Soxhlet tube containing 350 mL of n-hexane as a solvent and heated at 40°C - 60°C for 72 hrs, and the crude bio-oil was obtained. A rotary evaporator was used to remove the excess solvent, and finally, 60ml of bio-oil was obtained. The transesterification of *mimusops elengi* seed oil was done using Methanol (CH_3OH) and Potassium Hydroxide (KOH) as a catalyst, as shown in **Figure 1**.

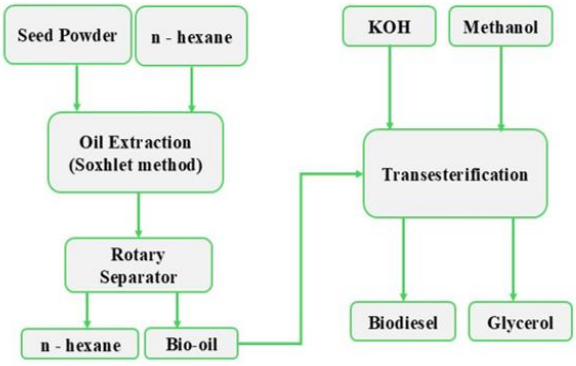

Figure 1. Transesterification Process of M. elengi Seed Oil

2.6. RSM for biodiesel reaction optimisation

Response Surface Methodology is a statistical modelling method used for multiple regression analysis using quantitative data obtained from the experiment. In this study, a 5-level, 4-factor central composite rotatable design (CCRD) was used to analyse the effect of the influence variable on the biodiesel conversion efficiency. The five levels in CCRD were –α, –1, 0, +1, and +α, in which axial points (±α) were for a factor and 0 for all other

aspects. A total of 30 experiments in a single block were used in CCRD, including 16 factorial points, eight axial points, and six center-point replications. The biodiesel conversion efficiency (FAME) is expressed as the function of influence variables based on Equation 1.

$$Y = \beta_{\circ} + \sum_{i=1}^{4} \beta_i X_i + \sum_{i=1}^{4} \beta_{ii} X^2_i + \sum_{i=1}^{3} \sum_{j=i+1}^{4} \beta_{ij} X_i X_j \quad (1)$$

The predicted RSM fame conversion is Y. The regression coefficients β0 is the intercept coefficient, β_i are linear coefficients, β_{ii} are quadratic coefficients β_{ij}, are interaction Coefficients, and X_i, X_j are independent influence variables. This study used four process influence variables: molar ratio (oil to methanol), catalyst (KOH), reaction temperature, and reaction time associated with the biodiesel conversion from *Mimusops Elengi* seed *via the* Transesterification process. These variables have five levels (- α, -1, 0, +1, and + α) representing the upper and lower range division. These variables input the statistical modelling in RSM to obtain the space point division of 30 runs. The process variables used in the CCRD of biodiesel production from *Mimusops Elengi* seed are shown in **Table 1**.

Table 1. CCRD-RSM process variables used in biodiesel production from Mimusops Elengi seeds

Factors	Symbols	Dimensions	Limit and code level				
Independent Variables			**-α**	**-1**	**0**	**+1**	**+α**
Molar Ratio	A	Mol/mol	3	4.5	6	7.5	9
Catalyst Conc.	B	Wt.%	0.5	0.7	0.9	1.1	1.3
Temperature	C	°C	32.5	40	47.5	55	62.5
Time	D	min	270	300	330	360	390

2.7. Artificial neural network study for biodiesel reaction optimisation

ANN is an alternative to the polynomial regression-based modeling tool, which models complex nonlinear relationships. It is a feed-forward, back-spread multi-facet insight (MLP) brain network examination through the Levenberg-Marquardt (LM) calculation to demonstrate the interaction boundaries of the base-catalyzed transesterification process by utilizing the brain network tool compartment of MATLAB 2015a (8.5.0.197613). The feed-forward network is straightforward and requires experimental yields to be incorporated into the model to explore the ANN working capacity. The chosen ANN has two layers of neurons: an info layer, a secret layer, and a result layer. The exaggerated digression sigmoid exchange works (Tansig), and direct exchange works (Purelin) are picked separately for info and result layers. The amount of information layer neurons is four, related to oil molar ratio (X1), catalyst concentration (X2), reaction temperature (X3), and reaction time (X4), and finally, the result layer is FAME (Biodiesel) content.

3. Results and discussion

3.1. Oil and ffa analysis

Based on the extensive literature, *mimusops elengi* seeds contain 20% of oil content, which is ideal for large-scale biodiesel production. In this study, the non-edible *Mimusops Elengi* seeds are well-suited for commercial biodiesel synthesis. Additionally, the free fatty acid (FFA) content of the *Mimusops Elengi* seed oil was found to be 0.37 mg KOH/g, which is relatively low and carried out a single-step transesterification process, as lower FFA levels improve biodiesel yield and quality.

3.2. Analysis of response surface methodology

The response surface method in DOE software utilizes regression model equations to generate and stimulate response data from the experimental set of values for FAME conversion, as shown in **Figure 3**. A total of 30 runs was performed in RSM; the oil to molar ratio varies between 3 to 9 (v/v), catalyst concentration of 0.5 to 1.1 (wt. %), temperature varies between 40 to 65 (°C), and times varies from 250 to 400 (min) respectively. The experimental analysis was performed in the laboratory with the help of the predicted values in Design Expert software. Run 4 gives the highest yield of 89.38% of experimental yield with the help of oil, a molar ratio of 1:7.5, catalyst concentration of 1.1 wt.%, temperature of 40°C, and reaction time of 300min. The predicted yield equals the experimental value of 89.38% and the ANN value, which would be used to compare RSM and experimental results. The value of ANN is 89.11%. Hence, the output yield of biodiesel at specific parameters gives 89% of the yield statistically and experimentally. The lowest value was noted in run 13, and the experimental yield of 61.67% with a catalyst concentration of 0.7 wt.%, oil-to-molar ratio of 1:7.5 v/v, temperature of 55°C and a reaction time of 360min with the help of experimental value the RSM yield gives 61.91% the difference of 0.24% takes place. Compared with ANN, it is 61.94%, a relatively 0.3% higher rate than RSM. The mean square error of RSM was noted as 0.40335, and the ANN value is 0.2356. the R^2 value of RSM is 0.99, and ANN is 0.99; both statistical results give 0.9 equal unity. The coded equation 2 obtained during stimulating the model is shown below.

$$\begin{aligned} \mathbf{Y} &= 80.60 + 9.02A + 4.3B - 0.1583C - 0.2617D - 0.1875AB \\ &+ 0.15125AC + 1.02AD + 0.1625BC + 0.08375BD + 0.2CD \\ &- 4.08167A^2 - 0.76417B^2 - 0.1279C^2 + 1.4183D^2 \end{aligned} \quad (2)$$

The statistical analysis performed by RSM with no transformation on experimental yield values results in equation 2 and fit summary, F(x) model, ANOVA table, diagnostics, and model graphs. The fit summary of the model indicates the quadratic model as the significant model with an F-value of 92.89 and a p-value less than 0.0001. The adjusted and predicted R^2 values obtained were 0.9851 and 0.9651, whereas the R^2 value of 0.9923

was obtained. The study of the ANOVA table suggests the model is significant. It produces the actual equation that can be utilized to get the predicted RSM values for biodiesel yield efficiency, and the exact equation simulation of data results in the R2 value being close to unity. The actual equation focuses on the model maximizing the adjusted R^2 and the predicted R^2. The expected set of RSM values is optimized to obtain the statistically optimum experimental yield of the biodiesel, as shown in **Table 3**. The statistical model analyzed using the response surface method suggests that the quadratic model is significant. Fit summary, sequential sum of the square, model statistics, ANOVA table, and diagnostic graphs were obtained using analysis of the model. The fit statistics table indicates that the predicted R^2 of 0.9657 is in reasonable agreement with the adjusted R^2 of 0.9851; i.e., the difference is less than 0.2. The adequate precision evaluates the signal-to-noise ratio. A ratio higher than four is recommendable. The ratio of 51.251 indicates a sufficient signal. This model can be utilized to explore the plan space. The selected model, i.e., the Quadratic vs. 2FI model, has an insignificant lack of fit.

Table 2a. ANOVA table for Quadratic Model of RSM

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	2992.54	14	213.75	137.82	< 0.0001	Significant
A-Molar Ratio	1950.85	1	1950.85	1257.85	< 0.0001	
B-Catalyst Content	444.45	1	444.45	286.57	< 0.0001	
C-Temperature	0.6017	1	0.6017	0.3879	0.5427	
D-Time	1.64	1	1.64	1.06	0.3196	
AB	0.5625	1	0.5625	0.3627	0.5560	
AC	0.3660	1	0.3660	0.2360	0.6341	
AD	16.65	1	16.65	10.73	0.0051	
BC	0.4225	1	0.4225	0.2724	0.6093	
BD	0.1122	1	0.1122	0.0724	0.7916	
CD	0.6400	1	0.6400	0.4127	0.5303	
A^2	456.96	1	456.96	294.63	< 0.0001	
B^2	16.02	1	16.02	10.33	0.0058	
C^2	0.4488	1	0.4488	0.2894	0.5985	
D^2	55.18	1	55.18	35.58	< 0.0001	
Residual	23.26	15	1.55			
Lack of Fit	16.18	10	1.62	1.14	0.4690	not significant
Pure Error	7.08	5	1.42			
Cor Total	3015.81	29				

Table 2b. Sequential Model Sum of Squares of RSM Analysed data

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	1.814E+05	1	1.814E+05			
Linear vs Mean	2397.54	4	599.38	24.24	< 0.0001	
2FI vs Linear	18.75	6	3.12	0.0990	0.9956	
Quadratic vs 2FI	576.25	4	144.06	92.89	< 0.0001	Suggested
Cubic vs Quadratic	15.37	8	1.92	1.70	0.2486	Aliased
Residual	7.90	7	1.13			
Total	1.844E+05	30	6145.95			

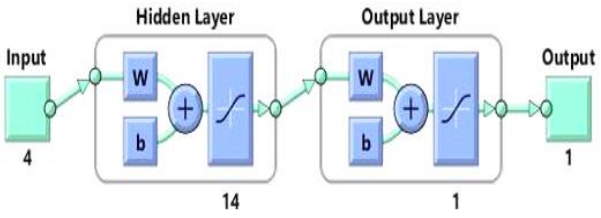

Figure 2. Neural Networks for training, testing, and validation

3.3. Analysis of ANOVA

The ANOVA analysis of the variance table showed that the Model F-value is 137.82, implying that the model is significant. There is only a 0.01% probability that an F-value this large could occur due to noise. A P-value under 0.0500 demonstrates that the model terms are significant. The values more prominent than 0.1000 indicate the model terms are insignificant, as shown in **Tables 2a and 2b**. The lack of fit F-value of 1.14 infers that the lack of fit is insignificant. There is a 46.90% opportunity that a lack of fit F-value is enormous, which could happen because of noise. A non-significant absence of fit is excellent. The actual factors can be utilized to forecast the reaction for each variable's given levels. The equation, in terms of actual factors, can be used to determine the response of each component at a given level, as shown in Equation 3. These RSM predicted value analyses correspond to R^2, adjusted R^2, and predicted R^2 towards 1.0000, indicating the model fit for optimization. The data results in 82.8662 % as the optimum yield at 1:7.47526 oil-methanol molar ratio, 0.768 by wt.% KOH concentration, 49.613°C temperature, and 340.55 min time.

$$\text{Actual Eq.} = 182.80273148147 + 20.223A + 49.90B - 0.276C - 1.24D - 0.625AB + 0.0134AC + 0.0226AD + 0.1083BC + 0.0139BD + 0.000894CD - 1.814A2 - 19.1042B2 - 0.002274C2 + 0.001576D2 \quad (3)$$

Similarly, artificial neural networks are another approach to obtain the predicted set of values. The MATLAB code with influence variables from the statistical table as input variable and experimental yield as output variable was used to train, test, and validate the data. The input variables were initially utilized to obtain ANN architecture by creating a new model with TRAINLM and LEARNGDM as training and adaptive learning functions. 2-layer 14 neurons, tansig and purlin, were used to prepare the model, as shown in **Figure 4**. The training of the data with 100 fails and six epochs was done along with input and output parameters to generate R^2 values. The R^2 value of 0.9992 was obtained as the highest. After training, the model was simulated to get the predicted values as output. The predicted values indicated as ANN yield percentage in the statistical table are utilized to obtain the Mean Square Error (MSE) between the experimental and ANN predicted data set, as shown in **Table 3**.

$$MSE = (1/n)\sum_{i=1}^{30}(E - A)^2 \quad (4)$$

$$RMSE = sqrt(MSE) \quad (5)$$

MATLAB digital tool was utilized to perform ANN analysis on the experimental data to train, test, and validate data set results in R^2 values of 0.83885, 0.99924, and 0.99295 for each. All R^2 values of 0.90246 were obtained. The resultant value for R^2 for the predicted set is 0.9992, indicating the model fit. The best validation obtained was 1.687 for six epochs, as shown in **Figure 2**.

Table 3. RSM and ANN predicted Process variables between experimental and statistical analysis

Std	Space Type	A:Molar Ratio mol/mol	B: Catalyst Content wt.%	C: Temp. (°C)	D: Time min	Experimental %	RSM Predicted %	ANN Predicted %
1	Factorial	4.5	0.7	40	300	64.45	64.58	64.21
2	Factorial	7.5	0.7	40	300	81.75	81.64	81.49
3	Factorial	4.5	1.1	40	300	73.17	74.07	74.01
4	Factorial	7.5	1.1	40	300	89.38	89.38	89.11
5	Factorial	4.5	0.7	55	300	64.52	64.24	64.56
6	Factorial	7.5	0.7	55	300	81.77	80.91	81.1
7	Factorial	4.5	1.1	55	300	72.93	73.38	72.96
8	Factorial	7.5	1.1	55	300	89.28	89.3	88.64
9	Factorial	4.5	0.7	40	360	62.15	62.45	63.02
10	Factorial	7.5	0.7	40	360	82.8	82.6	82.06
11	Factorial	4.5	1.1	40	360	70.17	70.18	70.85
12	Factorial	7.5	1.1	40	360	88.07	88.67	89.69
13	Factorial	4.5	0.7	55	360	61.67	61.91	61.94
14	Factorial	7.5	0.7	55	360	83.24	82.66	83.1
15	Factorial	4.5	1.1	55	360	70.96	71.38	71.32
16	Factorial	7.5	1.1	55	360	89.27	89.38	89.12
17	Axial	3	0.9	47.5	330	48.07	46.25	48.44
18	Axial	9	0.9	47.5	330	80.99	81.31	80.38
19	Axial	6	0.5	47.5	330	68.45	68.94	69.39
20	Axial	6	1.1	47.5	330	87.15	86.16	87.794
21	Axial	6	0.9	32.5	330	81.97	81.41	82.22
22	Axial	6	0.9	62.5	330	78.72	78.78	78.68
23	Axial	6	0.9	47.5	270	87.12	86.8	86.73
24	Axial	6	0.9	47.5	390	85.94	85.76	86.007
25	Center	6	0.9	47.5	330	80.15	80.61	80.69
26	Center	6	0.9	47.5	330	82.37	81.61	81.73
27	Center	6	0.9	47.5	330	81.74	81.61	81.69
28	Center	6	0.9	47.5	330	80.28	80.61	79.69
29	Center	6	0.9	47.5	330	79.45	80.61	79.69
30	Center	6	0.9	47.5	330	79.59	80.61	79.69
MSE							0.40335	0.235601
R^2							0.9923	0.9992

3.4. ANN analysis

An ANN is typically composed of a few neurons joined by connections. Through the synaptic weights of the connections between the neurons, the information is transmitted to other neurons after being processed within the neurons. A literature review demonstrates that ANN models outperform regression models regarding

prediction ability. Thus, ANN models are also developed to predict surface roughness. The preprocesses, model design, training, model simulation, and postprocesses are involved in ANN prediction models. The 30 experimental data sets are separated into three categories: testing, validation, and training. There are four data sets for testing, four for validation, and twenty-three for training. Numerous data sets are employed to train the models because it is evident that doing so speeds up ANN learning processing times and enhances the models' capacity for generalization. Studies of the network's performance using varying numbers of hidden neurons have been attempted. The best network is chosen based on the precision of the predictions made during the testing phase after a network is built, and each one is trained independently. Three-layer feed-forward neural networks with backpropagation are employed. The sigmoid activation function activates the input layer, the first layer.

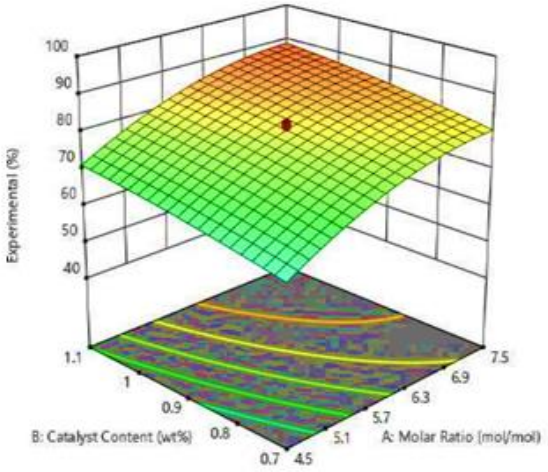

Figure 3. CCRD Plot between Catalyst Concentration (Wt. %) and Molar Ratio (mol/mol) for Biodiesel efficiency

Table 4. Model summary statistic of RSM

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	4.97	0.7950	0.7622	0.6888	938.66	
2FI	5.62	0.8012	0.6966	0.6758	977.77	
Quadratic	1.25	0.9923	0.9851	0.9657	103.42	Suggested
Cubic	1.06	0.9974	0.9892	0.9576	127.82	Aliased

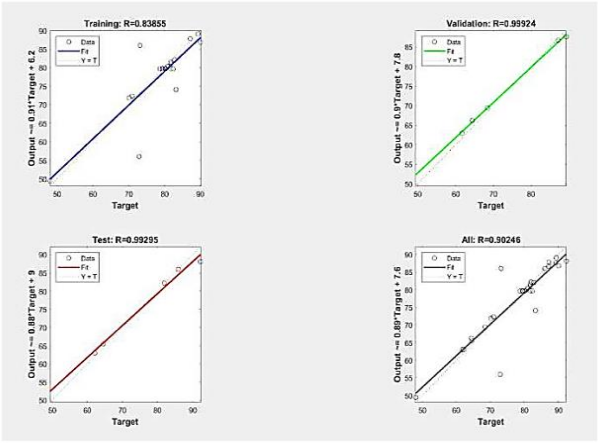

Figure 4. ANN Plots for Training, Testing and Target

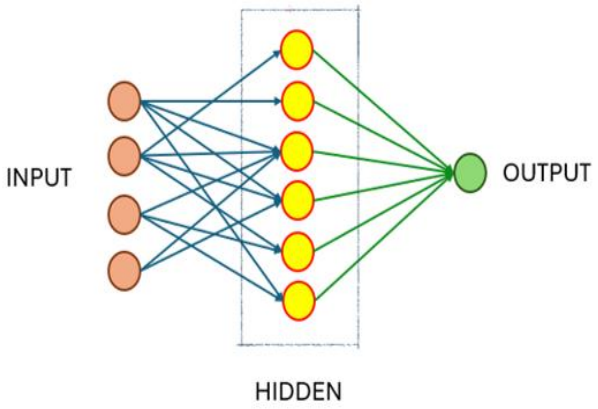

Figure 5. Network Layer of ANN

In contrast, the linear activation function activates the hidden layer and output layer, which are the second and third layers. Any function can be approximated by training a network of two transfer functions, with the first being tansig and the second being Purelin. The validation of the Artificial neural network and the predicted result with experimental value is performed. This method is used to predict biodiesel yield. The mean square error of ANN was 0.1667 less than RSM's, indicating that ANN has better predictive efficiency than RSM, as shown in **Table 4**. The maximum yield predicted was 89.1% for ANN and was closer to the experimental yield of 89%. The R^2 values for ANN and RSM were 0.9992 and 0.9923, respectively.

4. Conclusion

In conclusion, this study demonstrates the statistical optimization of biodiesel production from *Mimusops elengi* seeds using a potassium hydroxide-catalyzed transesterification process. The RSM and ANN studies were employed to model and predict the biodiesel yield, using different process variables such as oil-to-methanol molar ratio, catalyst concentration, reaction temperature, and time. The results showed that the ANN model had superior prediction accuracy, with a higher R^2 value of 0.9992 compared to 0.9923 for RSM and a mean square error of 0.2356, which is 0.1667 lower than RSM's. The optimum biodiesel yield of 89% was achieved at a 1:7.5 molar ratio optimized using RSM and ANN studies. These experimental findings recommend that ANN is a more effective and accurate analysis for predicting biodiesel yield.

Acknowledgment

The authors are grateful to acknowledge Vellore Institute of Technology, Tamil Nadu, India, for providing the research facilities to conduct the research.

Nomenclature

FAME	Fatty Acid Methyl Ester
RSM	Response Surface Methodology
ANN	Artificial Neural Network
BD	Biodiesel
KOH	Potassium Hydroxide
CCRD	Central Composite Rotatable Design
DOE	Design of Experiment
MLP	Multi Fact Insight
LM	Levenberg – Marquardt
MSE	Mean Square Error
TEA	Techno-economic analysis

References

Adama K. K. and Anani O.A. (2023). Experimental and Theoretical Assessment of Phenomena Linked with Separation and Purification of Biodiesel from Ricinus Communis Seed Oil. *Heliyon* **9**(6): e16536. doi:10.1016/j.heliyon.2023.e16536.

Al-dobouni I.A., Fadhil A.B. and Saeed I.K. (2016). Optimized Alkali-Catalyzed Transesterification of Wild Mustard (*Brassica Juncea L*) Seed Oil. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* **38**(15), 2319–2325. doi:10.1080/15567036.2014.1002952.

Al-Muhtaseb A.A. (2021). Utilisation of Non-Edible Source (Pongamia Pinnata Seeds Shells) for Producing Methyl Esters as Cleaner Fuel in the Presence of a Novel Heterogeneous Catalyst Synthesized from Waste Eggshells. *Molecules* **26**(19): 5772. doi:10.3390/molecules26195772.

Al-Muhtaseb A.A.., Osman A.I., Jamil F., Al-Riyami M., Al-Haj L., Alothman A.A., Kyaw H.H. *et al*. (2020). Facile Technique towards Clean Fuel Production by Upgrading Waste Cooking Oil in the Presence of a Heterogeneous Catalyst. *Journal of King Saud University - Science* **32**(8): 3410–3416. doi:10.1016/j.jksus.2020.10.001.

Anjum S.S., Prakash O. and Pal A. (2019). Conversion of Non-Edible Argemone Mexicana Seed Oil into Biodiesel through the Transesterification Process. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* **41**(19): 2356–63. doi:10.1080/15567036.2018.1563244.

Athar M. and Zaidi S. (2020). A Review of the Feedstocks, Catalysts, and Intensification Techniques for Sustainable Biodiesel Production. *Journal of Environmental Chemical Engineering* **8**(6): 104523. doi:10.1016/j.jece.2020.104523.

Choudhury H.A., Chakma S. and Moholkar V.S. (2014). Mechanistic Insight into Sonochemical Biodiesel Synthesis Using Heterogeneous Base Catalyst. *Ultrasonics Sonochemistry* **21**(1): 169–81. doi:10.1016/j.ultsonch.2013.04.010.

Chutia G.P., Chutia S., Kalita P. and Phukan K. (2023). Xanthium Strumarium Seed as a Potential Source of Heterogeneous Catalyst and Non-Edible Oil for Biodiesel Production. *Biomass and Bioenergy* **172**, 106773. doi:10.1016/j.biombioe.2023.106773.

Esan A.O., Adeyemi A.D. and Ganesan S. (2020). A Review on the Recent Application of Dimethyl Carbonate in Sustainable Biodiesel Production. *Journal of Cleaner Production* **257**, 120561. doi:10.1016/j.jclepro.2020.120561.

Fadhil A.B., Sedeeq S.H. and Al-Layla N.M.T. (2019). Transesterification of Non-Edible Seed Oil for Biodiesel Production: Characterization and Analysis of Biodiesel. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* **41**(7): 892–901. doi:10.1080/15567036.2018.1520367.

Gami B., Pathak S. and Parabia M. (2012). Ethnobotanical, Phytochemical and Pharmacological Review of Mimusops Elengi Linn. *Asian Pacific Journal of Tropical Biomedicine* **2**(9), 743–48. doi:10.1016/S2221-1691(12)60221-4.

Garg A. and Jain S. (2020). Process Parameter Optimization of Biodiesel Production from Algal Oil by Response Surface Methodology and Artificial Neural Networks. *Fuel* **277**, 118254. doi:10.1016/j.fuel.2020.118254.

Habib M.S., Tayyab M., Zahoor S. and Sarkar B. (2020). Management of Animal Fat-Based Biodiesel Supply Chain under the Paradigm of Sustainability. *Energy Conversion and Management* **225**, 113345. doi:10.1016/j.enconman.2020.113345.

Hájek M., Skopal F., Vávra A. and Kocík J. (2017). Transesterification of Rapeseed Oil by Butanol and Separation of Butyl Ester. *Journal of Cleaner Production* **155**, 28–33. doi:10.1016/j.jclepro.2016.07.007.

Hamza M., Ayoub M., Shamsuddin R.B., Mukhtar A., Saqib S., Zahid I., Ameen M. *et al*. (2021). A Review on the Waste Biomass Derived Catalysts for Biodiesel Production. *Environmental Technology & Innovation* **21,** 101200. doi:10.1016/j.eti.2020.101200.

Jamil F., Kumar P.S.M., Al-Haj L., Myint M.T.Z. and Al-Muhtaseb A.A. (2021). Heterogeneous Carbon-Based Catalyst Modified by Alkaline Earth Metal Oxides for Biodiesel Production: Parametric and Kinetic Study. *Energy Conversion and Management: X* **10**, 100047. doi:10.1016/j.ecmx.2020.100047.

Jume B.H., Gabris M.A., Nodeh H.R., Rezania S. and Cho J. (2020). Biodiesel Production from Waste Cooking Oil Using a Novel Heterogeneous Catalyst Based on Graphene Oxide Doped Metal Oxide Nanoparticles. *Renewable Energy* **162**, 2182–2189. doi:10.1016/j.renene.2020.10.046.

Kesharvani S., Katre S., Pandey S., Dwivedi G., Verma T.N. and Baredar P. (2024). Optimizing Biodiesel Production from Karanja and Algae Oil with Nano Catalyst: RSM and ANN Approach. *Energy Engineering* **121**(9), 2363–88. doi:10.32604/ee.2024.052523.

Kirubakaran M. and Selvan V A.M. (2018). A Comprehensive Review of Low Cost Biodiesel Production from Waste Chicken Fat. *Renewable and Sustainable Energy Reviews* **82**. 390–401. doi:10.1016/j.rser.2017.09.039.

Krupakaran R.L., Hariprasad T. and Gopalakrishna A. (2018). Impact of Various Blends of Mimusops Elengi Methyl Esters on Performance and Emission Characteristics of a Diesel Engine. *International Journal of Green Energy* **15**(7): 415–26. doi:10.1080/15435075.2018.1469496.

Kumar N. and Chauhan S.R. (2013). Performance and Emission Characteristics of Biodiesel from Different Origins: A Review. *Renewable and Sustainable Energy Reviews* **21**, 633–58. doi:10.1016/j.rser.2013.01.006.

Paswan A.K., Kesharvani S., Suneja S.K., and Dwivedi G.. (2023). Performance and Emissions Characteristics of CI Engine Fueled with Blends of Diesel and Polanga Biodiesel. *Materials Today: Proceedings* **78**, 647–55. doi:10.1016/j.matpr.2022.12.069.

Malani R.S., Patil S., Roy K., Chakma S., Goyal A. and Moholkar V.S. (2017). Mechanistic Analysis of Ultrasound-Assisted Biodiesel Synthesis with Cu 2 O Catalyst and Mixed Oil Feedstock Using Continuous (Packed Bed) and Batch (Slurry) Reactors. *Chemical Engineering Science* **170**, 743–55. doi:10.1016/j.ces.2017.03.041.

Naveenkumar R. and Baskar G. (2020). Optimization and Techno-Economic Analysis of Biodiesel Production from Calophyllum Inophyllum Oil Using Heterogeneous Nanocatalyst. *Bioresource Technology* **315**, 123852. doi:10.1016/j.biortech.2020.123852.

Panwar N.L., Kaushik S.C. and Kothari S. (2011). Role of Renewable Energy Sources in Environmental Protection: A Review. *Renewable and Sustainable Energy Reviews* **15**(3): 1513–24. doi:10.1016/j.rser.2010.11.037.

Potrč S, Lidija L., Martin M. and Kravanja Z. (2021). Sustainable Renewable Energy Supply Networks Optimization – The Gradual Transition to a Renewable Energy System within the European Union by 2050. *Renewable and Sustainable Energy Reviews* **146**, 111186. doi:10.1016/j.rser.2021.111186.

Rao R., Zubaidha P., Kondhare D., Reddy N. and Deshmukh S. (2012). Biodiesel Production from *Argemone Mexicana* Seed Oil Using Crystalline Manganese Carbonate. *PJCT* **14**(1): 65–70. doi:10.2478/v10026-012-0061-x.

Rezania S., Oryani B., Park J., Hashemi B., Yadav K.K., Kwon E.E., Hur J. and Cho J. (2019). Review on Transesterification of Non-Edible Sources for Biodiesel Production with a Focus on Economic Aspects, Fuel Properties and by-Product Applications. *Energy Conversion and Management* **201**, 112155. doi:10.1016/j.enconman.2019.112155.

Sangeetha B., Priya S.M., Pravin R., Tamilarasan K. and Baskar G. (2023). Process Optimization and Technoeconomic Assessment of Biodiesel Production by One-Pot Transesterification of Ricinus Communis Seed Oil. *Bioresource Technology* **376**, 128880. doi:10.1016/j.biortech.2023.128880.

Sierchuła J., Weissbach D., Huke A., Ruprecht G., Czerski K. and Da˛browski M.P. (2019). Determination of the Liquid Eutectic Metal Fuel Dual Fluid Reactor (DFRm) Design – Steady State Calculations. *International Journal of Energy Research* **43**(8), 3692–3701. doi:10.1002/er.4523.

Stigka E.K., Paravantis J.A. and Mihalakakou G.K. (2014). Social Acceptance of Renewable Energy Sources: A Review of Contingent Valuation Applications. *Renewable and Sustainable Energy Reviews* **32**, 100–106. doi:10.1016/j.rser.2013.12.026.

Vávra A., Hájek M. and Skopal F. (2017). The Removal of Free Fatty Acids from Methyl Ester. *Renewable Energy* **103**, 695–700. doi:10.1016/j.renene.2016.10.084.

Vonortas A. and Papayannakos N. (2014). Comparative Analysis of Biodiesel versus Green Diesel. *WIREs Energy and Environment* **3**(1), 3–23. doi:10.1002/wene.78.

Yusuf N.N.A.N., Kamarudin S.K. and Yaakub Z. (2011). Overview on the Current Trends in Biodiesel Production. *Energy Conversion and Management* **52**(7): 2741–51. doi:10.1016/j.enconman.2010.12.004.