IRASS Journal of Multidisciplinary Studies
https://irasspublisher.com/journal-details/IRASSJMS
ISSN *(Online)* 3049-0073

Artificial Neural Network Modelling for Production of Biodiesel from Waste Cooking Oil

P. Kanakasabai[1], Saikat Banerjee[2], D. Sridevi[3] & S. Sivamani[4*]

[1-2-*4]College of Engineering and Technology, Engineering Department, University of Technology and Applied Sciences, Salalah, Oman

[3]IT Department, SRM Valliammai Engineering College Tamil Nadu, India

Corresponding Author: S. Sivamani

College of Engineering and Technology, Engineering Department, University of Technology and Applied Sciences, Salalah, Oman

Article History

Received: 19 / 07 / 2026

Accepted: 28 / 08 / 2026

Published: 12 / 09 /2026

Abstract: Artificial neural networks (ANN) are bioinspired algorithms used in various engineering applications. The objective of this present study is to create a model algorithm for biodiesel synthesis from the collected waste cooking oil utilizing artificial neural networks (ANN). The factors consider to be influencing the biodiesel production are concentrations of solutions, time and temperature, pH of the solution, and agitation speed. In previous trials, methanol to oil ratio, sodium hydroxide to oil ratio, in addition to reaction temperature were taken as in terms of independent type of variables and % biodiesel yield inulin as a dependent variable. The results reveal that the 3-10-1 architecture of ANN provides goodness of fit to predict the percentage yield of biodiesel. The prediction ability of ANN is assessed by the coefficient of determination (R^2). The resultant R^2 value shows that the ANN predicted values fitted well to the percentage yield of biodiesel.

Keywords: *Inulin, Artificial neural network, biodiesel, Extraction, Percentage yield.*

How to Cite in APA format: Kanakasabai, P., Banerjee, S., Sridevi, D. & Sivamani, S. (2026). Artificial Neural Network Modelling for Production of Biodiesel from Waste Cooking Oil. *IRASS Journal of Multidisciplinary Studies, 3(9), 19-25. http://doi.org/10.67564/IRASSJMS.v3.i9.0188*

Introduction

Artificial Neural Networks (ANN) consist of networked nodes, referred to as neurons, that exchange signals and process information. The weight of each neuron controls the degree to which it affects the other neurons to which it is attached. In order to teach ANNs to forecast data output accurately, data is fed to them, and they are then given the opportunity to modify the weights of their connections. Even if the new data is different from the data that trained the ANNs, they can still be utilised to forecast or make judgements based on the previously learned data. Applications for artificial neural networks (ANNs) are numerous and include image identification, machine translation, speech recognition, natural language processing, and medical diagnosis [1].

Biodiesel produced from bio resource is reflected to be a renewable and eco-friendly substitute for conventional type of diesel fuel, with waste cooking oil being a prevalent and natural source for its manufacturing. [2-4]. Waste cooking oil, also known as used cooking oil (UCO) or recycled cooking oil, is a valuable resource for producing biodiesel because it can help reduce environmental pollution and lessen the strain on fossil fuel resources [5-8]. Waste cooking oil is collected from various sources such as restaurants, households, and food processing facilities. The collected oil needs to be properly filtered and strained to remove any food particles, water, as well as impurities[9-11]. This step is essential to ensure the quality or class of the biodiesel manufactured. Transesterification is stated to be the chemical process used to convert the waste cooking oil into biodiesel[12-15]. The process comprises the reaction of triglycerides (which are mainly fats and oils) within the oil in the presence of alcohol, usually methanol or ethanol, facilitated by a catalyst. Sodium hydroxide (NaOH) or potassium hydroxide (KOH) is frequently utilized as a catalyst.[16-18].

After the transesterification reaction, the mixture contains two phases: biodiesel and glycerol (a byproduct). These two phases need to be separated. Glycerol is typically heavier and settles at the bottom. The biodiesel as required by the process is further cleaned to eliminate any residual portion of contaminants and catalyst remnants. [19-22]. The washed biodiesel may still contain trace impurities, so it goes through a refining process to meet fuel quality standards. This step typically includes drying and filtration. The final product, biodiesel, is ready for storage and distribution. It can be used as a blend with conventional diesel fuel or used in its pure form (B100)[22-24]. Biodiesel may be utilized in multiple mixtures with standard type of diesel fuel. Prevalent blends comprise B5 (5% biodiesel) and B20 (20% biodiesel).

The quality characteristics of residual cooking oil utilized in the form of feedstock is essential. Contaminants, including water, food particles, and other contaminants, can adversely affect the process of making biodiesel and the quality characteristics of the end product. [25][26]. Proper filtration and pre-treatment are essential to ensure high-quality feedstock. In the transesterification type of process, methanol is consider to be cast-off to react by means of the triglycerides in the oil. It's important to consider methanol recovery and recycling to reduce costs and environmental impact. Methanol recovery systems can be integrated into biodiesel production facilities. Glycerol is produced as a byproduct of the particular transesterification process. Proper disposal or utilization of glycerol is necessary. It may be cast-off in various applications, such as in soap production, animal feed, or further processing to yield value-added products[27][28].

Proper storage and handling are crucial to prevent contamination and degradation of the fuel over time. Biodiesel has a higher gel point than regular diesel fuel, which means it can gel in cold temperatures. Blending with petrol diesel or using additives can help improve cold-weather performance [29][30].While biodiesel is reflected a more globally responsive alternative to traditional diesel, the sustainability of feedstock sourcing is essential. It's important to ensure that the manufacturing of waste cooking oil and the cultivation of feedstocks (e.g., sunflower oil or canola for biodiesel) are environmentally responsible and sustainable [31][32].

A multiple input variable model can predict several output variables using an ANN model. This approach to understanding the system, which does not necessitate prior knowledge of process links, diverges from conventional modeling approaches[32]. While numerical methods for solving differential equations do not require lengthy iterative calculations, a well-trained artificial neural network (ANN) can predict outcomes much more quickly than traditional simulation programs or mathematical models. However, choosing the right neural network topology is crucial for both simplicity and accuracy of the model [33][34].

Reviews of the literature indicate that a wide range of scientific works have been written about the production of biodiesel, beginning with pure vegetable oils, animal fats, pure cooking and non-edible vegetable oils, waste and denatured vegetable oils, and algal oils. However, ANN based research on producing biodiesel from used blend vegetable oils is lacking. Hence, the current study uses an ANN technique to investigate the effect of extraction parameters on biodiesel production. The present work focusses on optimization of biodiesel yield from the blend of waste cooking oil of sunflower and mustard oil by varying methanol to oil molar ratio, sodium hydroxide to oil mass percentage of and temperature using feed forward back propagation ANN analysis.

Materials and experimental methods

In Salalah, Oman, waste cooking oil (WCO) was collected from restaurants and residential areas. All of the materials in the work were obtained from VWR International and were of analytical quality. The water for this experiment was made by double distillation. All materials were used in their natural state, barring any exceptional situations.

To be used in the transesterification process, WCO was gathered in Salalah, Oman, from restaurants and residential areas. Using 40 m filter sheets and low-grade heating to 50oC, the solid and floating contaminants were removed from the samples. To eliminate any moisture content, the filtered samples were heated to 65 degrees Celsius for 30 minutes. Methanol and sodium hydroxide were used to create the methoxide (CH_3ONa). Following the combination of methoxide and filtered, moisture-free WCO, the transesterification process was carried out inside a batch reactor. Following the vacuum evaporation system's methanol evaporation, the residual triglycerides were transesterified for an hour at 65°C in a reaction system with 1.5% (w/w) sodium hydroxide and a molar ratio of 1:6 between the methanol and oil. A separating funnel was used to separate the process product from the byproduct. The biodiesel yield was computed by dividing the quantity of produced biodiesel by the mass of oil.

ANN modelling

All the experimental details and procedures related to the production of biodiesel from waste cooking oil are given in the materials and experimental methods. The ANN model has been established for biodiesel synthesis from leftover cooking oil.The multi-layer feed-forward ANN is a reliable technique for non-linear regression analysis. There is one input layer, at least one hidden layer, and one output layer for a feed-forward, multi-layered neural network, respectively. While the neurons in the output layer may have either linear or non-linear activating functions, those in the hidden layer have non-linear activating functions.

A parameter weight is linked to the connections between two layers of neurons. The threshold parameter known as bias is present in each neuron in the hidden as well as output layers. The ANN is trained using experiment data while the model development process continues. An ANN is trained by setting its parameters using input-output data patterns.

The error is decreased by the use of a back-propagation technique. Targets derived from accessible experimental data are compared to each ANN's output. To decrease mistakes between the network output and target output, the system modifies the weight of the internal connections. Until the mistakes converge to a given value, training is still in progress. Algebraically mapping the input-output data is the result of the trained ANN model. It is possible to feed the trained network with input data that should allow it to reasonably predict the output.

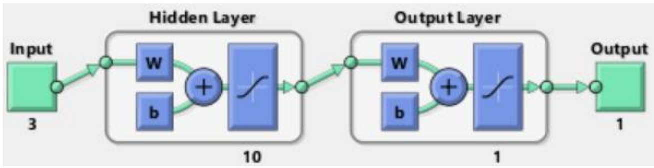


Figure 1. Architecture of 3-10-3 Ann For Prediction of % Yield of Biodiesel From Waste Cooking Oil

An ANN's architecture is made up of three layers: an output layer which contains response variables, a hidden layer that contains neurons, and an input layer that contains input parameters. Weights link the layers together. The optional bias types of layers are introduced as intercepts to the hidden as well as output layers in polynomial equations. The determination coefficient (R^2) is employed in error analysis to evaluate the efficacy of ANN modelling. The lowest error might be achieved by carefully choosing the right network type, number of neurons, hidden layers, training, modification, studying, performance, as well as activation functions.

MATLAB R2022a is utilized for ANN modeling purpose. This study used a single type of input, multiple type of output artificial neural network by means of feed-forward as well as backward propagation, gradient descent, momentum weight, bias learning function, and Levenberg-Marquardt algorithm. R^2 is employed to perform the error analysis through the application of sigmoidal tangent (TANSIG) activation functions for the hidden and output layers. Because the system consists of one output component in the output layer, ten neurons in the hidden layer, and three input factors in the input layer, this study used a 3-10-1 design. One hidden layer with ten neurons has been selected since more than 99% efficacy has been attained in fewer iterations.

Normalization of the input data supplied into the ANN tool occurs as TANSIG processes values between -1 and +1. Next, the input data is subjected to training, testing, and validation in the following order: 70:15:15. First, the data is denormalized from -1 to +1 to obtain the actual output. Next, after comparing the actual output data with the anticipated data, an error value is computed. When the least quantity of error is reached, the iteration comes to a conclusion. If not, training, testing, and validation iterations are carried out to assess weights and bias. Figure 1 depicts the architecture of the artificial neural network used in this study.

Weights, wij, where i is the number of input factor as well as j is the hidden layer neuron number, are used to connect the input layer to the hidden layer. Bias parameter to the jth neuron in the hidden layer is represented by B1j. Equation (1) expresses the generalised equation from input to hidden layers as

$$H_j = \sum_{i,j=1}^{i,j=3,10} w_{ij} X_i + B_{1j} \qquad (1)$$

where, Xi represents ith input factor

Weights, wjk, which stand for the output layer's output variable number k, connect the hidden layer to the output layer. Biases to the kth factor of the output layer is represented by B2k. Equation (18) represents the generalised equation from hidden to output layers as

$$Y_k = \sum_{i=1}^{9} \tanh(H_j) * w_{jk} + B_{2k} \qquad (2)$$

where, Y_k represents kth output factor. To conduct training, the parameters were set as depicted in Figure 2. We used MATLAB's default configuration parameters without making any changes.

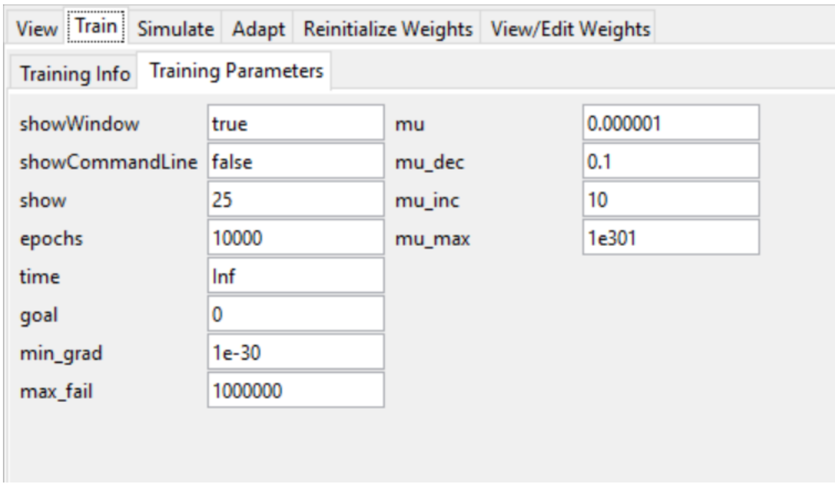


Figure 2. Training Parameters For Performing Ann Model

Results and Discussion

Table 1. Experimental And Ann Predicted Values Of % Yield Of Biodiesel From Waste Cooking Oil

S.No	Methanol to oil molar ratio (MOMR) X1	NaOH to oil mass percentage (NOMR) X2	Reaction Temperature (°C) X3	Biodiesel Yield (%) YExp	YANN
1	6	1.5	65	96	96
2	7	1.5	60	86	82.89
3	6	1.5	65	95	96
4	6	2	70	76	76
5	6	1.5	65	97	96
6	6	1	70	86	86
7	5	1.5	70	76	76
8	5	1.5	60	81	81
9	6	1.5	65	96	96
10	6	1	60	86	86
11	6	2	60	81	81.11
12	7	1.5	70	81	77.61
13	7	2	65	81	81.84
14	5	2	65	76	76

15	5	1	65	81	81
16	7	1	65	86	87.17
17	6	1.5	65	96	96

Table 1 shows the percentage biodiesel yield as a function of three independent variables: MOMR, NOMR, and reaction temperature, and the percentage yield of biodiesl as a dependent variable. The input layer contains the MOMR, NOMR, and reaction temperature. The output layer contains % biodiesel yield response variables. Table 1 shows that ANN-predicted % inulin yield values are closer to % inulin yield experimental values.

Figure 3 illustrates the ANN's success in forecasting the percentage biodiesel yield using the single-input, multiple-output model's Levenberg-Marquardt method. The minimal number of iterations—133—is needed to get the desired performance. The required performance is attained in 13 iterations in minimum time.

The samples used to build the model are collectively referred to as the training dataset; performance is qualified using the testing as well as validation dataset. The weights linking the input parameter entering to the hidden layer are displayed in Table 2, and Table 3 shows the weights connecting the output layer to the output.

Figure 3. Progress of Ann for Prediction Of The % Biodeisel Yield

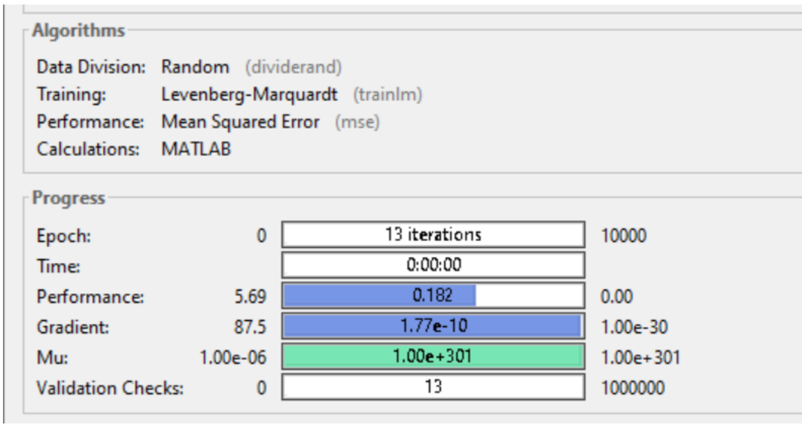


Table 2 The Weights Of Inputs And Bias To The Ann Model For Prediction

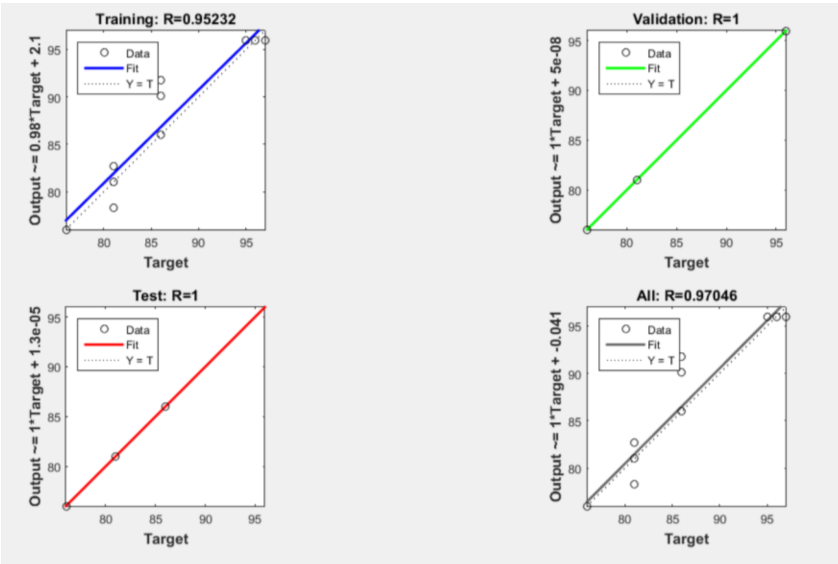
Neuron	Weight input layer			
	Methanol to oil molar ratio	NaOH to oil mass percentage	Reaction Temperature	Bias to hidden layer
1	-1.99	-2.39	-3.31	-6.16
2	-3.51	-0.10	-1.62	-6.09
3	0.19	1.25	1.15	3.73
4	-0.76	-4.39	0.43	-5.71
5	3.61	5.84	-3.39	1.37
6	-6.38	-3.64	1.55	0.71
7	-1.94	0.61	1.65	-0.89
8	2.10	1.68	0.29	3.64
9	2.60	0.38	-0.56	3.63
10	0.63	0.19	-0.868	4.66

Table 3 The Weights Of Output To The Ann Model For Prediction

Neuron	Weight output layer	
	% Biodiesel yield	Bias to output layer
1	7.54	-0.74
2	1.44	
3	-0.25	
4	6.86	
5	-0.08	
6	2.06	
7	-5.17	
8	-0.02	
9	0.49	
10	2.06	

Consequently, the good, sufficient, and higher values of coefficient (R) of the ANN predicted and experimental responses imply that the newly designed ANN could predict the % yield of biodiesel. Figure 4 displays experimental and projected % yield levels for each experiment, as predicted by ANN. The correlation coefficients (R) of training, testing, and validation are found to be 0.95232, 1, and 1, respectively. Overall, the value was found to be 0.97046, which shows a direct and strong correlation. It is obvious from the preceding figures that the trained neural network approximates experimental results effectively. The present work is limited only to the range of experimental values studied. The existing work could be extended beyond the studied range of experimental values.

Figure 4. Correlation Coefficients Of Training, Testing, Validation, And All Prediction Set Of % Biodiesel Yield Parameters From Waste Cooking Oil



Conclusion

The present work focusses on developing a model for biodiesel production from waste cooking oil using ANN. Biodiesel was extracted from waste cooking oil using methanol and sodium hydroxide. Methanol to oil ratio, sodium hydroxide to oil percentage and reaction temperature were taken as independent variables % biodiesel yield as dependent variable. The overall correlation coefficient (R) of 0.97046 reveals that 3-10-1 architecture of ANN provides goodness of fit to predict % biodiesel yield from chicory.

Acknowledgment

The authors would be grateful to the management of University of Technology and Applied Sciences, Salalah, Oman and SRM Valliammai Engineering College, Tamilnadu, India for their support in this research.

References

1. Rosa, J. P., Guerra, D. J., Horta, N. C., Martins, R. M., Lourenço, N. C., Rosa, J. P., ... & Lourenço, N. C. (2020). Overview of artificial neural networks. Using artificial neural networks for analog integrated circuit design automation, 21-44.

2. Chhetri, A. B., Watts, K. C., & Islam, M. R. (2008). Waste cooking oil as an alternate feedstock for biodiesel production. Energies, 1(1), 3-18.

3. Gashaw, A., & Teshita, A. (2014). Production of biodiesel from waste cooking oil and factors affecting its formation: A review. International journal of renewable and sustainable energy, 3(5), 92-98.

4. Yaakob, Z., Mohammad, M., Alherbawi, M., Alam, Z., & Sopian, K. (2013). Overview of the production of biodiesel from waste cooking oil. Renewable and sustainable energy reviews, 18, 184-193.

5. Singh, D., Sharma, D., Soni, S. L., Inda, C. S., Sharma, S., Sharma, P. K., & Jhalani, A. (2021). A comprehensive review of biodiesel production from waste cooking oil and its use as fuel in compression ignition engines: 3rd generation cleaner feedstock. Journal of Cleaner Production, 307, 127299.

6. Borugadda, V. B., & Goud, V. V. (2012). Biodiesel production from renewable feedstocks: Status and opportunities. Renewable and Sustainable Energy Reviews, 16(7), 4763-4784.

7. de Araújo, C. D. M., de Andrade, C. C., e Silva, E. D. S., & Dupas, F. A. (2013). Biodiesel production from used cooking oil: A review. Renewable and sustainable energy reviews, 27, 445-452.

8. Vignesh, P., Kumar, A. P., Ganesh, N. S., Jayaseelan, V., & Sudhakar, K. (2021). A review of conventional and renewable biodiesel production. Chinese journal of chemical engineering, 40, 1-17.

9. Huang, D., Zhou, H., & Lin, L. (2012). Biodiesel: an alternative to conventional fuel. Energy Procedia, 16, 1874-1885.

10. Panadare, D. C. (2015). Applications of waste cooking oil other than biodiesel: a review. Iranian Journal of Chemical Engineering (IJChE), 12(3), 55-76.

11. Foo, W. H., Koay, S. S. N., Chia, S. R., Chia, W. Y., Tang, D. Y. Y., Nomanbhay, S., & Chew, K. W. (2022). Recent advances in the conversion of waste cooking oil into value-added products: A review. Fuel, 324, 124539.

12. Abd Rabu, R., Janajreh, I., & Honnery, D. (2013). Transesterification of waste cooking oil: Process optimization and conversion rate evaluation. Energy Conversion and Management, 65, 764-769.

13. Banerjee, A., & Chakraborty, R. (2009). Parametric sensitivity in transesterification of waste cooking oil for biodiesel production—A review. Resources, Conservation and Recycling, 53(9), 490-497.

14. Lam, M. K., Lee, K. T., & Mohamed, A. R. (2010). Homogeneous, heterogeneous and enzymatic catalysis for transesterification of high free fatty acid oil (waste cooking oil) to biodiesel: a review. Biotechnology advances, 28(4), 500-518.

15. Maneerung, T., Kawi, S., Dai, Y., & Wang, C. H. (2016). Sustainable biodiesel production via transesterification of waste cooking oil by using CaO catalysts prepared from chicken manure. Energy Conversion and Management, 123, 487-497.

16. Van Kasteren, J. M. N., & Nisworo, A. P. (2007). A process model to estimate the cost of industrial scale biodiesel production from waste cooking oil by supercritical transesterification. Resources, Conservation and Recycling, 50(4), 442-458.

17. It involves reacting the triglycerides (fats and oils) in the oil with an alcohol, typically methanol or ethanol, in the presence of a catalyst. Sodium hydroxide (NaOH) or potassium hydroxide (KOH) is commonly used as a catalyst.

18. Shahla, S., Cheng, N. G., & Yusoff, R. (2010). An overview on transesterification of natural oils and fats. Biotechnology and Bioprocess Engineering, 15, 891-904.

19. Keera, S. T., El Sabagh, S. M., & Taman, A. R. (2011). Transesterification of vegetable oil to biodiesel fuel using alkaline catalyst. Fuel, 90(1), 42-47.

20. Hájek, M., & Skopal, F. (2010). Treatment of glycerol phase formed by biodiesel production. Bioresource technology, 101(9), 3242-3245.

21. Zhou, W., & Boocock, D. G. B. (2006). Phase distributions of alcohol, glycerol, and catalyst in the transesterification of soybean oil. Journal of the American Oil Chemists' Society, 83(12), 1047-1052.

22. Pisarello, M. L., Maquirriain, M., Olalla, P. S., Rossi, V., & Querini, C. A. (2018). Biodiesel production by transesterification in two steps: Kinetic effect or shift in the equilibrium conversion?. Fuel Processing Technology, 181, 244-251.

23. Mendow, G., Veizaga, N. S., Sánchez, B. S., & Querini, C. A. (2011). Biodiesel production by two-stage transesterification with ethanol. Bioresource Technology, 102(22), 10407-10413.

24. Micic, R. (2020). Storing, distribution and blending of biodiesel. Agricultural Engineering International: CIGR Journal, 22(2), 105-111.

25. Abdalla, I. E. (2018). Experimental studies for the thermo-physiochemical properties of Biodiesel and its blends and the performance of such fuels in a Compression Ignition Engine. Fuel, 212, 638-655.

26. Singh, D., Sharma, D., Soni, S. L., Inda, C. S., Sharma, S., Sharma, P. K., & Jhalani, A. (2021). A comprehensive review of biodiesel production from waste cooking oil and its use as fuel in compression ignition engines: 3rd generation cleaner feedstock. Journal of Cleaner Production, 307, 127299.

27. Atadashi, I. M., Aroua, M. K., Aziz, A. A., & Sulaiman, N. M. N. (2012). The effects of water on biodiesel production and refining technologies: A review. Renewable and sustainable energy reviews, 16(5), 3456-3470.

28. Kiss, A. A., & Ignat, R. M. (2012). Enhanced methanol recovery and glycerol separation in biodiesel production–DWC makes it happen. Applied Energy, 99, 146-153.

29. Mythili, R., Venkatachalam, P., Subramanian, P., & Uma, D. (2014). Recovery of side streams in biodiesel production process. Fuel, 117, 103-108.

30. Misra, R. D., & Murthy, M. S. (2011). Blending of additives with biodiesels to improve the cold flow properties, combustion and emission performance in a compression ignition engine—A review. Renewable and sustainable energy reviews, 15(5), 2413-2422.

31. Shrestha, D. S., Van Gerpen, J., & Thompson, J. (2008). Effectiveness of cold flow additives on various biodiesels, diesel, and their blends. Transactions of the ASABE, 51(4), 1365-1370.

32. KOLAKOTİ, A. (2020). Optimization of biodiesel production from waste cooking sunflower oil by taguchi and ann techniques. Journal of Thermal Engineering, 6(5), 712-723.

33. Ghobadian, B., Rahimi, H., Nikbakht, A. M., Najafi, G., & Yusaf, T. F. (2009). Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. Renewable energy, 34(4), 976-982.

34. Najafi, G., Ghobadian, B., Yusaf, T., & Rahimi, H. (2007). Combustion analysis of a CI engine performance using waste cooking biodiesel fuel with an artificial neural network aid. American Journal of Applied Sciences, 4(10), 756-764.

35. Gul, M., Shah, A. N., Aziz, U., Husnain, N., Mujtaba, M. A., Kousar, T.& Hanif, M. F. (2022). Grey-Taguchi and ANN based optimization of a better performing low-emission diesel engine fueled with biodiesel. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 44(1), 1019-1032.

36. Dharmalingam, B., Balamurugan, S., Wetwatana, U., Tongnan, V., Sekhar, C., Paramasivam, B., Sriariyanun, M. (2023). Comparison of neural network and response surface methodology techniques on optimization of biodiesel production from mixed waste cooking oil using heterogeneous biocatalyst. Fuel, 340, 127503.

37. Kesharvani, S., Katre, S., Pandey, S., Dwivedi, G., Verma, T. N., & Baredar, P. (2024). Optimizing Biodiesel Production from Karanja and Algae Oil with Nano Catalyst: RSM and ANN Approach. Energy Engineering, 121(9).