

**MACHINE LEARNING TECHNOLOGY FOR SELECTION OF RAW OIL
FOR BIODIESEL PRODUCTION WITH REDUCED WASHING**

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Electronics and Communication

Engineering

By

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**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade “A” by NAAC

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING **BONAFIDE CERTIFICATE**

This is to certify that this Project Report is the bonafide work **ADITHYA SRIDHAR (39130009)** and **J. BHARATH KUMAR (39130067)** who carried out the project entitled " **MACHINE LEARNING TECHNOLOGY FOR SELECTION OF RAW OIL FOR BIODIESEL PRODUCTION WITH REDUCED WASHING** " under our supervision from November 2022 to April 2023.

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ABSTRACT

Biodiesel has the potential to make transportation fuels more sustainable than traditional fossil fuels. Washing biodiesel is a crucial step in its preparation, as it removes excess alcohol, catalyst, and soap from the fuel. Water is mixed with the biodiesel to accomplish this process. Efficient modeling tools are necessary for designing, optimizing, monitoring, and controlling the highly complex biodiesel production process. Machine learning (ML) techniques have shown promise in predicting outcomes compared to traditional methods, due to the complex data involved. The focus of this work is to develop an ML model for predictive analysis of the number of wash water cycles required for biodiesel production, based on properties of Waste Cooking Oil (WCO), intermediate biodiesel, and wash water. This model is important for determining the number of wash cycles required for biodiesel production, allowing raw oils that require a higher number of wash cycles to be avoided. This study uses a Sugeno controller based ANFIS algorithm to design the prediction model. As there was insufficient data pertaining to washing, all the data used in this experiment was obtained through physical experiments. The results were then validated against the practical data.

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STANDARDS FOLLOWED:

This table shows selected requirements for 100% biodiesel (B100), as listed in ASTM D6751:

Property	Reference Test Methods*	Grade No.1-B S15	Grade No.1-B S500	Grade No.2-B S15	Grade No.2-B S500
Sulfur, % mass (ppm), max	D5453	0.0015 (15)	0.05 (500)	0.0015 (15)	0.050 (500)
Cold soak filterability, s, max	D7501	200	200	360	360
Monoglycerides, % mass, max	D6584	0.40	0.40	-	-
Requirements for All Grades					
Calcium and Magnesium, combined, ppm, max	EN14538	5	5	5	5
Flash point (closed cup), °C, min	D93	93	93	93	93
Alcohol Control: One of the following must be met					
(1) Methanol content, mass%, max	EN14110	0.2	0.2	0.2	0.2
(2) Flash point,	D93	130	130	130	130

Property	Reference Test Methods*	Grade No.1-B S15	Grade No.1-B S500	Grade No.2-B S15	Grade No.2-B S500
°C, min					
Water and sediment, % volume, max	D2709	0.050	0.050	0.050	0.050
Kinematic viscosity, mm²/s, 40°C	D445	1.9-6.0	1.9-6.0	1.9-6.0	1.9-6.0
Sulfated ash, % mass, max	D874	0.020	0.020	0.020	0.020
Copper strip corrosion	D130	No. 3	No. 3	No. 3	No. 3
Cetane number, min	D613	47	47	47	47
Cloud point, °C	D2500	Report	Report	Report	Report
Carbon residue^a, % mass, max	D4530	0.050	0.050	0.050	0.050
Acid number, mg KOH/g, max	D664	0.50	0.50	0.50	0.50
Free glycerin, % mass, max	D6584	0.020	0.020	0.020	0.020
Total glycerin, % mass, max	D6584	0.240	0.240	0.240	0.240
Phosphorus content, % mass,	D4951	0.001	0.001	0.001	0.001

Property	Reference Test Methods*	Grade No.1-B S15	Grade No.1-B S500	Grade No.2-B S15	Grade No.2-B S500
max					
Distillation temperature, 90% recovered (T90)b, °C, max	D1160	360	360	360	360
Sodium and potassium, combined, ppm, max	EN14538	5	5	5	5
Oxidation stability, hrs, min	EN15751	3	3	3	3

This table shows requirements for 6% biodiesel (B6) to 20% biodiesel (B20) as listed in ASTM D7467:

Property	Reference Test Methods*	Grade B6 to B20 S15 B6 to B20 S500 B6 to B20 S5000		
Acid number, mg KOH/g, max	D664	0.3	0.3	0.3
Viscosity, mm²/s at 40°C	D445	1.9-4.1a	1.9-4.1a	1.9-4.1a
Flash point, °C, min	D93	52b	52b	52b
Cloud point, °C, max or LTFT/CFPP, °C, max	D2500, D4539,	c	c	c

	D6371			
Sulfur Content, (µg/g or ppm)	D5453	15	—	—
mass %, max	D2622	—	0.05	—
mass %, max	D129	—	—	0.50
Distillation temperature, °C, 90% evaporated, max	D86	343	343	343
Ramsbottom carbon residue on 10% bottoms, mass %, max	D524	0.35	0.35	0.35
Cetane number, min	D613	40	40	40
One of the following must be met:				
(1) Cetane index, min	D976-80	40	40	40
(2) Aromaticity, vol %, max	D1319-03	35	35	—
Ash Content, mass %, max	D482	0.01	0.01	0.01
Water and Sediment, vol %, max	D2709	0.05	0.05	0.05
Copper Corrosion, 3 h @ 50°C, max	D130	No. 3	No. 3	No. 3
Biodiesel Content, % (V/V)	D7371	6.–20.	6.–20.	6.–20.
Oxidation Stability, hours, min	EN15751	6	6	6

Lubricity, HFRR @ 60°C, (micron μm), max	D6079	520	520	520
Conductivity (pS/m) or Conductivity Units (C.U.), min	D2624/D4308	25	25	25

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO BIODIESEL

The development of renewable fuels has recently become a pressing issue due to the limitations of non-renewable fossil fuels [1]. Non-renewable fossil fuels are becoming increasingly problematic as they are highly contaminating to the environment, have a limited supply, are becoming more expensive, and are unable to keep up with the ever-increasing global energy demands. This is compounded by the fact that the world's fossil fuel reserves are dwindling rapidly, while the emissions from the use of these fuels contribute significantly to the greenhouse effect and global warming. To address these challenges, various approaches have been explored and exploited, including the development of renewable energies such as wind energy, geothermal energy, and biofuels. Among these, biodiesel has emerged as a promising alternative to petro-diesel [2]. Biodiesel is a diesel fuel substitute that can be made from a variety of oils, fats, and greases. Its development is of interest for a number of reasons, such as providing an additional market for vegetable oils and animal fats and decreasing dependence on imported oil since the fuel feedstocks can be grown domestically. Biodiesel is a renewable source of energy that can help reduce greenhouse gas emissions and minimize the carbon footprint [3]. It has been found to produce less air pollution, in terms of exhaust emissions, than diesel made from fossil fuels . Biodiesel is also less toxic than traditional diesel, making it a safer and healthier option for humans and the environment. In conclusion, the development of renewable fuels, particularly biodiesel, is essential in addressing the limitations of non-renewable fossil fuels and mitigating the effects of global warming [1].

1.2 FEEDSTOCKS FOR BIODIESEL

Feedstocks for biodiesel are chosen based on price and performance. Common feedstocks include soybean oil, canola oil, palm oil, and animal fats, among others. Each feedstock has different characteristics and may be better suited for certain conditions. For example, some feedstocks may perform better in cold temperatures than others. However, the prices of these feedstocks can fluctuate

depending on demand, as they also have alternative uses and markets [4]. It's important to note that biodiesel is not the same as straight vegetable oil or animal fat. Using these fuels in a normal diesel engine can eventually cause damage to the engine [4]. Biodiesel is specifically designed to be used in engines that run on diesel fuel. It's made through a process called transesterification, where vegetable oil or animal fat is reacted with an alcohol (usually methanol or ethanol) and a catalyst (usually sodium hydroxide or potassium hydroxide). This process separates the glycerin from the oil or fat, resulting in a thinner product that works better in a diesel engine [4]. In contrast to biodiesel, bioethanol is an alcohol made from fermented sugar and is designed to be used in engines that run on gasoline. It's made through a process of fermentation, distillation, and dehydration [4]. While biodiesel and bioethanol are both renewable fuels, they are not interchangeable. In conclusion, choosing the right feedstock for biodiesel production is critical to achieving the desired performance and price. Additionally, it's important to understand that biodiesel is not the same as straight vegetable oil or animal fat, nor is it the same as bioethanol. By utilizing the transesterification process, biodiesel can be produced from a variety of feedstocks and used as a renewable alternative to traditional diesel fuel [4].

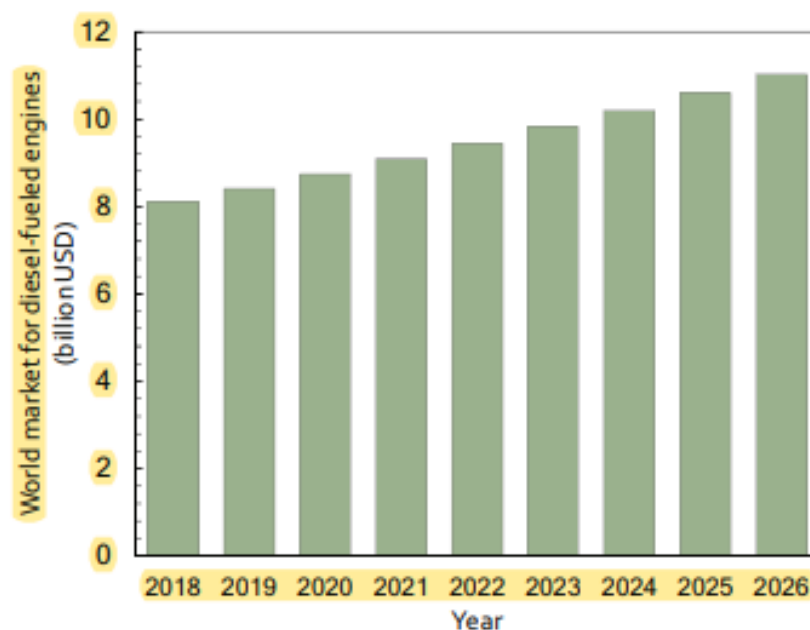


Fig. 1.1. The world market for diesel-fueled engines from 2018 to 2026 [49].

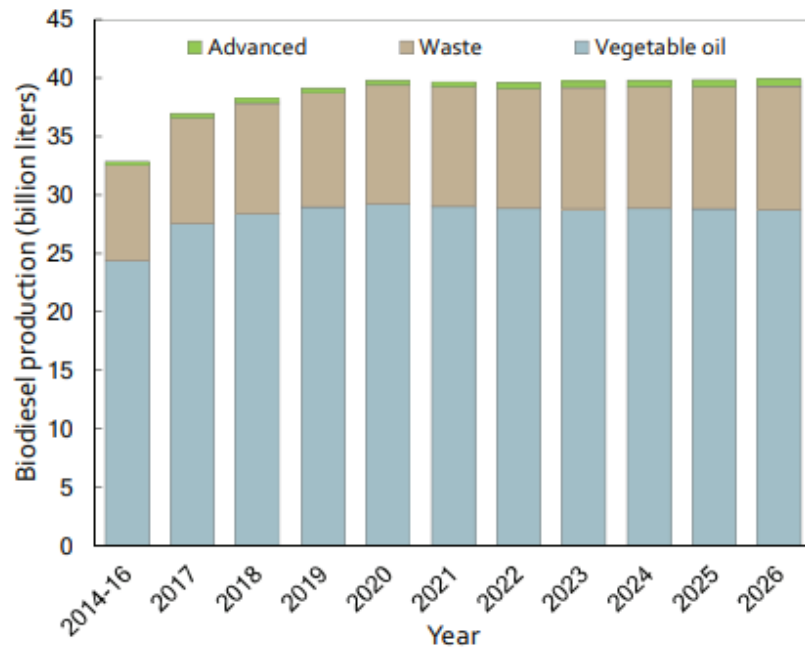


Fig. 1.2. Global biodiesel production by feedstocks [5]. Advanced biodiesels refer to biodiesels produced from agricultural residues, forest residues, and energy crops. The first column shows the average amount of biodiesel produced between 2014– 2016.

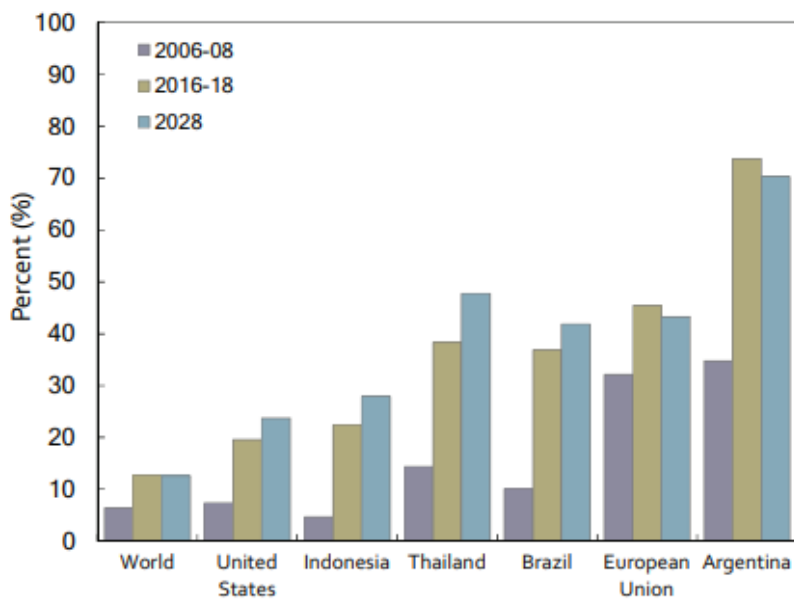


Fig. 1.3. Share of vegetable oil used for biodiesel production [5]. Some of the most environmentally friendly biodiesel feedstocks are used cooking oil and waste grease. The cleanest and easiest to work with is used cooking oil, also called waste vegetable oil [6].

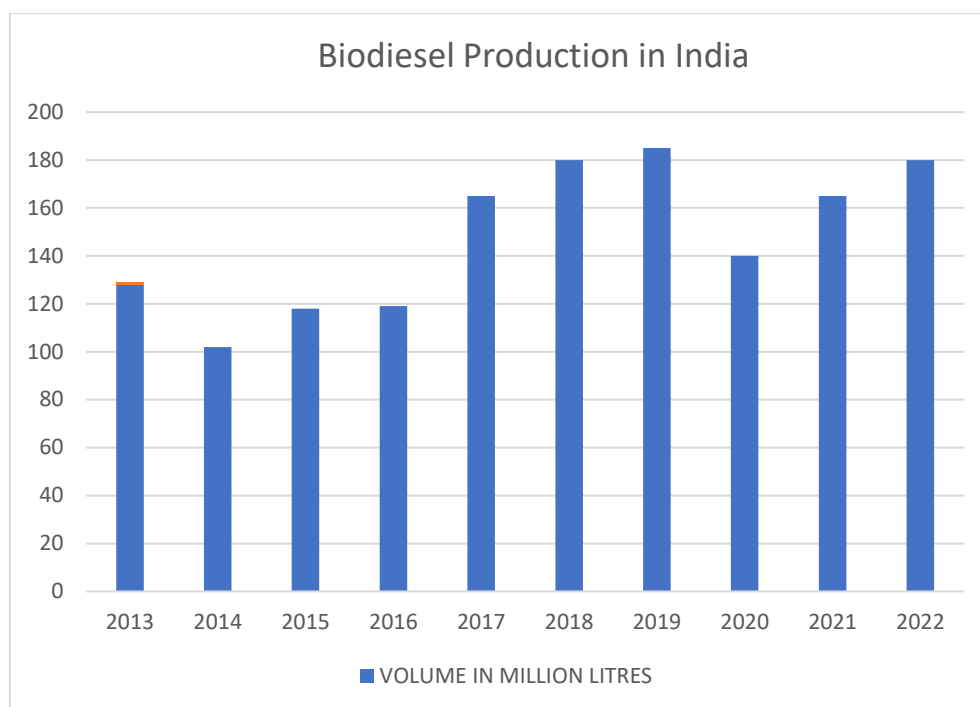


Fig 1.4. Biodiesel production in India over the last 10 years (Statista)

As the figures 1.1-1.4 suggest, there has been an increasing upward trend in the production of biodiesel over the last few years. Fig 1.3 also shows that Waste Cooking Oil biodiesel has also been increasingly adopted worldwide. However, India continues to lag behind in the successful largescale adoption of biodiesel.

Table 1.1. Physiochemical properties of waste cooking oil and biodiesel

Parameters	ASTM standards	WCO properties	WCOBD properties
Density (g/cc)	ASTM D792	0.925	0.875
Kinematic viscosity @ 40 °C (cSt)	ASTM D445	9.38	2.18
Flash point by PMCC method (°C)	ASTM D93	245	189
Fire point by PMCC method (°C)	ASTM D93	261	202
Copper strip corrosion @60 °C	ASTM D130	1a (slight tarnish)	1a (slight tarnish)
Cloud point (°C)	ASTM D2500	12	8

Pour point (°C)	ASTM D2500	4	2
Moisture content (%)	ASTM D2709	2.6	0.021
Acid value	ASTM D664	0.11%	0.218 mg NaOH/g of biodiesel
Calorific value (cal/g)	ASTM D480913	9,598.5	8,522.978

1.3 CHALLENGES IN BIODIESEL PRODUCTION

Biodiesel production from used oils and greases faces a significant challenge due to the high percentage of free fatty acids (FFAs) in the feedstock [7]. Triglycerides in fats and oils comprise three fatty acid molecules attached to a glycerol molecule. In used oils and greases, some of the triglycerides break down, and the fatty acids separate from the glycerol molecule, resulting in free fatty acids. The high level of free fatty acids reacts with the alkali catalyst in biodiesel production to form soap instead of biodiesel. This reaction reduces the level of free catalyst, slows down the transesterification reaction, and inhibits the separation of ester from glycerin. Furthermore, as soap must be removed and discarded, more soap formation leads to less biodiesel.

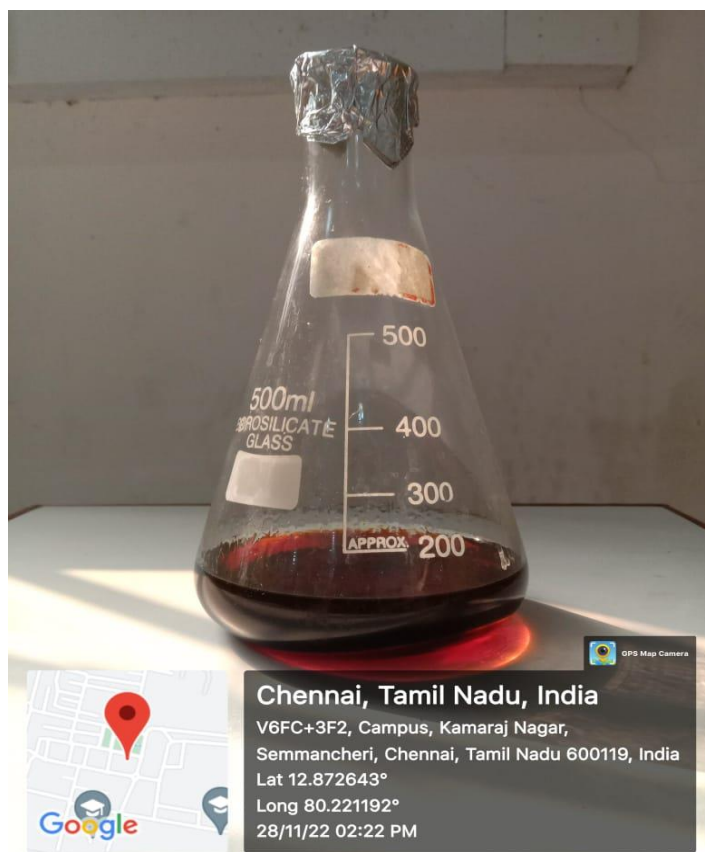


Fig 1.5. Soap or Glycerol that is produced during the transesterification process

When the FFA content of a feedstock is less than 3-4%, additional catalysts can be added to convert FFAs to soap and remove it. However, when the FFA content exceeds 10-15%, as in the case of used cooking oil and trap grease, traditional alkali-catalyzed transesterification is not effective [7]. In such cases, vacuum distillation can be used to remove the FFAs, and the oil can be processed normally, with FFAs being sold separately as animal feed or esterified. Alternatively, an acid catalyst, such as sulfuric or hydrochloric acid, can be used to convert the FFAs to esters, followed by alkali-catalyzed transesterification to convert the triglycerides to esters. However, this approach results in water formation during the conversion of FFAs to esters, leading to soap formation during the alkali-catalyzed process. To address this problem, an acid pre-treatment process can be used to reduce the FFA content of the oil or grease before alkali-catalyzed transesterification [8]. The acid catalyst and alcohol are added and reacted, and the mixture is allowed to reach equilibrium. Then, the methanol, water, and acid portion that separates are removed, and if necessary,

more acid and alcohol are added, and the process is repeated until the FFA level is less than 1%. After this pre-treatment process, the reaction continues with alkali-catalyzed transesterification, resulting in fuel that meets ASTM specifications for acid value. While the acid pre-treatment process is effective in reducing FFAs, it has some disadvantages. The acid can cause damage to metal tanks, and extra methanol is required because it becomes contaminated with water during the process. A distillation tower is needed to separate the water from the methanol for recovery and reuse. To overcome this problem, Teflon or plastic-coated tanks or super-alloy tanks can be used.

When feedstocks have a high percentage of free fatty acids (FFAs), traditional alkali-catalyzed transesterification cannot be used for biodiesel production. However, an alternative process called glycerolysis can be used for feedstocks with more than 10% FFAs [9]. In glycerolysis, glycerin is added at 400°F to react with the FFAs and form monoglycerides, which can then undergo a standard alkaline catalyst transesterification process. Although glycerolysis is effective, it can be expensive due to the high heat involved, which requires a high-pressure boiler and trained boiler operator. Also, vacuum must be applied while heating to remove water that is formed during the reaction. Solid acid catalysts are a newer technology that can be used for FFAs conversion. In this process, the FFAs are converted to esters using a solid acid catalyst packed in a canister. Unlike the traditional process, the acid does not contaminate the oil and does not need to be removed at the end. However, excess methanol used to force the chemical equilibrium to give a complete reaction is contaminated by water formed by the esterification reaction. To make the process economically viable and environmentally sustainable, the contaminated methanol must be recycled through a distillation process to remove water.

1.4 BIODIESEL WASHING AND PROBLEMS ASSOCIATED WITH IT

The washing process is a critical step in biodiesel production, necessary for improving its properties. Once the purification process is complete, residual water in the biodiesel is evaporated by heating. The purification must comply with the biodiesel specifications, such as ASTM D6751 or EN 14214. There are two recognized methods of purification, dry and wet washing [10]. Dry washing

involves using adsorbent compounds and cation-exchange to remove impurities. While membrane extraction can also be used, it is an expensive process with a short operation time that increases the overall cost of biodiesel production. Moreover, biodiesel produced through dry washing may not meet standard specifications [10]. Conversely, wet washing with water, including stirring and bubble methods, is commonly used for biodiesel purification as it is simple, economical, and effectively removes soaps due to their water solubility [11]. The impurities are considered removed when the washing water is clear. Wet refining technologies meet EN14214 in terms of the methanol and free glycerol levels required in biodiesel fuel, but the process results in wastewater discharge, leading to environmental pollution and raising environmental concerns. In conventional biodiesel production plants, approximately 0.2-3 L of raw biodiesel wastewater is discharged for every 1L of biodiesel produced, which has an alkaline pH, high concentrations of chemical oxygen demand (COD), biochemical oxygen demand (BOD), and fats, oils, and greases (FOG) [12]. Currently, several processes have been developed to treat biodiesel wastewater including biological [13], chemical and physical processes.

1.5 OBJECTIVE

The study aims to address several important objectives in the field of biodiesel production. Firstly, the main goal is to develop an intelligent algorithm that can accurately predict the number of wash cycles required to attain pure biodiesel. This algorithm will be developed using machine learning techniques to analyze data from previous biodiesel production processes and identify patterns and trends in the purification process. By predicting the optimal number of wash cycles, the algorithm can help reduce the amount of time and resources required for the purification process. Secondly, the study will examine existing machine learning techniques to find the most suitable one for the task at hand. This involves comparing various algorithms and selecting the one that offers the best performance in terms of accuracy, efficiency, and scalability. By selecting the most appropriate machine learning technique, the study aims to ensure that the intelligent algorithm developed can provide reliable and accurate predictions of the number of wash cycles required to attain pure biodiesel. Another important

objective of the study is to make biodiesel production cheaper. By reducing the number of physical experiments required for the purification process, the study aims to reduce the costs associated with biodiesel production. The intelligent algorithm developed can help reduce the number of physical experiments required by predicting the optimal number of wash cycles needed for purification. Finally, the study aims to save time by reducing the need for redundant physical experimentation. By developing an intelligent algorithm that can accurately predict the number of wash cycles required, the study aims to reduce the amount of time required for purification, thereby accelerating the overall biodiesel production process. This will also reduce the number of resources needed for physical experimentation, which can be redirected towards other areas of research and development.

1.6 SIGNIFICANCE OF THIS PROJECT

Biodiesel production involves several steps, and one of the most crucial ones is the washing process. However, the conventional methods of washing can result in a significant loss of water, time, and resources. In today's world, where environmental concerns are on the rise, the wastage of resources is not only financially impractical but also unsustainable. Therefore, finding a way to make this process more efficient is of utmost importance. Machine learning has emerged as a powerful tool that can help improve the efficiency of biodiesel production. By using intelligent algorithms, machine learning can optimize the washing process, thereby reducing the amount of water required and the time taken. This, in turn, can significantly reduce the cost of production and make biodiesel more economically viable. Moreover, the use of machine learning can also reduce the need for redundant physical experimentation, which is not only time-consuming but also costly. By analyzing large amounts of data, machine learning can identify patterns and make accurate predictions about the number of wash cycles required to attain pure biodiesel. This can save both time and resources, making the process of biodiesel production more sustainable and efficient. Overall, the application of machine learning in biodiesel production can have significant benefits, both economically and environmentally.

1.7 BACKGROUND OF STUDY

In their paper titled "Machine learning technology in biodiesel research: A review" [14], M. Aghbashlo, W. Peng, M. Tabatabaei, and colleagues conducted an in-depth analysis of existing machine learning techniques for various stages of biodiesel production. The comprehensive review provided a solid foundation for the current research, highlighting the potential of machine learning to streamline the biodiesel production process. The well-structured and organized paper demonstrated that machine learning and biodiesel production are not separate entities, but can be effectively combined to create a more efficient production chain. The authors' insights and findings were critical in laying the groundwork for the development of an intelligent algorithm for predicting the number of wash cycles needed to attain pure biodiesel, as well as examining existing machine learning techniques to determine the most suitable one. Overall, the study underscored the importance of incorporating machine learning into biodiesel production to improve efficiency and reduce waste of resources, including water and time.

1.8 PROBLEM STATEMENT

To plan a model that accurately predicts the number of wash cycles required in biodiesel production, several factors need to be considered. The physio-chemical properties of the oil sample, the intermediate biodiesel, and the wash water all play a critical role in the washing process. Therefore, the model must be trained to take these factors into account to produce accurate predictions. Implementing a machine learning algorithm for this purpose is complex and requires patience and extensive work. The model must be trained on a large dataset of experimental results until it is almost perfect and can make accurate predictions most of the time. The accuracy of the model is crucial to ensure that the biodiesel produced meets the required specifications. The model should be easy to use so that even those with little technical expertise can handle it with ease. It should be designed in a way that enables quick processing of large datasets, which is essential for large-scale biodiesel production. Ensuring that the algorithm is space-efficient will also minimize the hardware requirements, making it more accessible to small-scale producers.

CHAPTER 2 LITERATURE SURVEY

2.1. RECENT TRENDS IN APPLICATION OF MACHINE LEARNING IN BIODIESEL PRODUCTION

Biodiesel systems are inherently complex, uncertain, and nonlinear, and traditional modeling approaches often fail to capture the intricacies of these systems. To overcome this challenge, researchers have turned to data-driven machine learning (ML) technology as a more efficient alternative. Among the various ML techniques available, artificial neural network (ANN) technology has been found to be particularly useful in biodiesel research. As depicted in Figure 2.1, there has been a notable increase in the number of studies utilizing ML technology in biodiesel research over the past decade. This trend can be attributed to a number of factors, including the growing interest in using ML technology in various fields, as well as the availability and maturity of artificial intelligence methods. ANNs have been shown to be effective in modeling the complex relationships between input and output variables in biodiesel systems, making them a valuable tool for predicting key properties and optimizing process conditions.

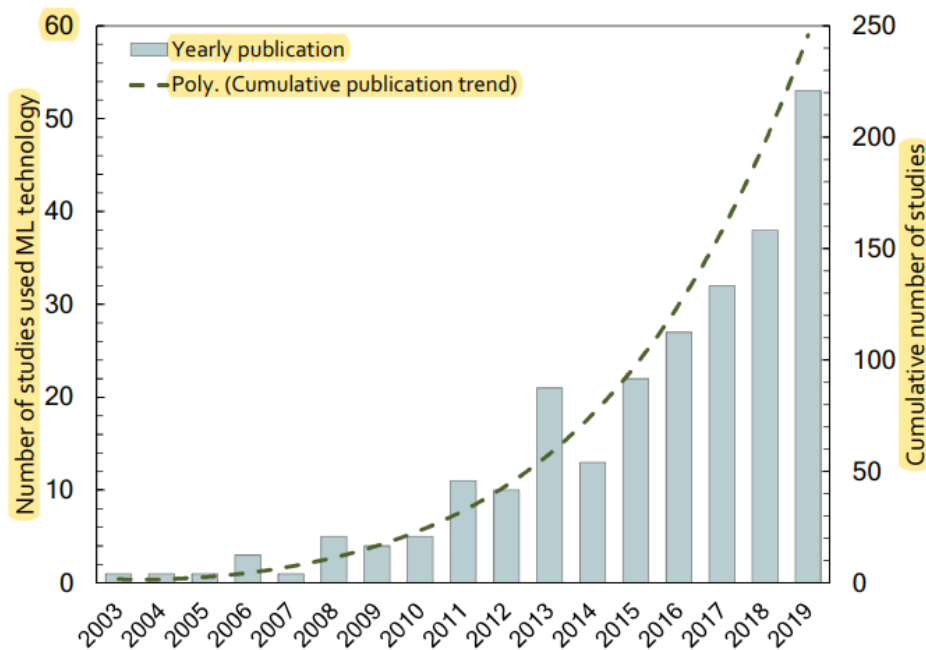


Fig. 2.1. The number of studies that dealt with the use of ML technology in biodiesel research [14].

Additionally, ANN models can be trained using large datasets, allowing researchers to capture a wide range of system behaviors and explore complex

interactions that are difficult to capture with traditional modeling approaches. Overall, the increasing use of ML technology in biodiesel research highlights the importance of innovative approaches in addressing complex and dynamic systems. By leveraging the power of data-driven modeling techniques such as ANNs, researchers can gain new insights into biodiesel systems and develop more efficient and sustainable processes.

2.2. ML APPLICATION IN RENEWABLE ENERGY

Machine learning and artificial neural networks (ANN) have been frequently employed in renewable energy studies. In one review, Kalogirou (2001) [15] provides several examples of ANN applications in solar energy, including modelling and designing a solar steam generating plant, estimating a parabolic trough collector intercept factor and local concentration ratio, and predicting the performance of solar water heating systems. Meanwhile, Wang et al. (2019) [16] conducted a comprehensive review of deep learning-based forecasting methods for renewable energy, categorizing them into deep belief network, stack auto-encoder, deep recurrent neural network, and other approaches. They also discussed data preprocessing techniques and error post-correction methods to improve forecasting accuracy and highlighted current research activities, challenges, and future research directions. Furthermore, several recent papers focused exclusively on ANN and ML techniques in solar and wind energy have garnered recognition globally [17-20].

The definition of biodiesel provided by the American Society for Testing and Materials (ASTM) states that it is a mixture of fatty acid alkyl esters that are produced from sustainable sources such as vegetable oils, waste animal fats, and waste oils, Zahira et.al. (2013) [21]. The production of biodiesel involves a series of steps including oil extraction, feedstock pretreatment, esterification or transesterification reaction, product separation, biodiesel washing, unreacted alcohol recovery, glycerin neutralization, and biodiesel purification. This process is illustrated in Figure 6.

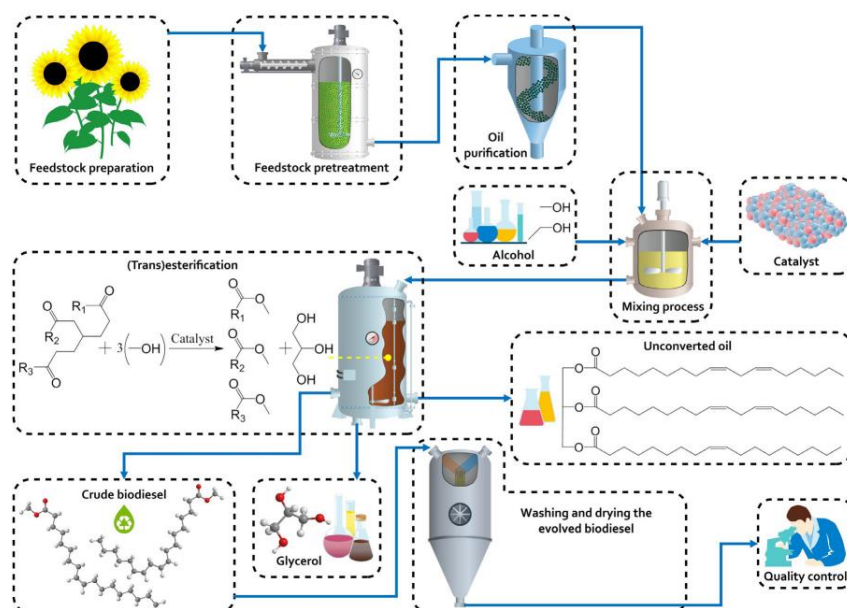


Fig. 2.2. Critical steps of a typical biodiesel production process [14]

2.3. ML APPLICATION IN PREDICTING BIODIESEL YIELD

In the field of biodiesel production, it is essential to have reliable modelling tools to accurately predict the yield. Soji-Adekunle et al. (2019) [22] conducted a study using artificial neural network (ANN) and response surface methodology (RSM) as modelling tools to predict the waste cooking oil methyl esters (WCOME) yield obtained from alkali-catalyzed methanolysis of waste cooking oil (WCO). The inputs given were catalyst amount, methanol/oil molar ratio, reaction temperature, and reaction time, and the output was the FAME yield. Another study by Avinash and Murugesan (2018) [23] aimed to compare the prediction ability of RSM and Multi-Layer Perceptron Neural Network (MLPNN) methods in modelling the FAME yield. They concluded that the trained MLPNN model was superior to the RSM model in simulating the FAME content. In a similar study, Najafi et al. (2018) [24] modelled the FAME/FAEE yield using RSM, MLPNN, radial basis function neural network (RBFNN), and adaptive Neuro-fuzzy inference system (ANFIS) models. The results indicated that the RBFNN model outperformed the developed MLPNN and ANFIS models in estimating the process yield. Corral Bobadilla et al. (2018) [25] employed the support vector machine (SVM) model with linear, polynomial, and RBF kernels for predicting the viscosity, turbidity, density, HV, and FAME yield while optimizing the reaction conditions using the GA paradigm. Their research

suggested that the SVM-GA combination with the polynomial and RBF kernels successfully modeled and optimized the transesterification process.

Naderloo et al. (2017) [26] conducted a study to model the energy productivity and ratio in the production of biodiesel from waste cooking oil using an ANFIS model. Their findings suggested that the ANFIS model was more accurate in predicting the energy ratio and productivity compared to the linear regression model. Mostafaei et al. (2016) [27] compared the efficiency of RSM and ANFIS models in predicting the transesterification yield achieved in an ultrasonic reactor. Both models demonstrated good predictions, but the ANFIS model was more precise, indicating its usefulness in modeling and optimization. Aghbashlo et al. (2017) [28] aimed to perform a multi-objective fuzzy modeling and optimization of a low power, high-frequency piezo-ultrasonic reactor used for biodiesel production from waste cooking oil. They used three different fuzzy optimization methods interfaced with the ANFIS modeling system to minimize the specific energy consumption of the reactor and achieve a conversion efficiency of >96.5% as per the ASTM standard on yield.

The authors utilized two ANFIS models to correlate conversion efficiency and specific energy consumption with three input variables, namely reaction temperature, ultrasonic irradiation time, and methanol/oil molar ratio. To optimize the transesterification process of waste cooking oil, three multi-objective optimization techniques were employed, namely the fuzzy systems with independent, interdependent, and locally-modified interdependent objectives. Both ANFIS models accurately predicted the output parameters, and the locally-modified interdependent objectives fuzzy system performed better in optimizing the transesterification process of WCO compared to the other two fuzzy systems.

2.4. ML APPLICATION IN PREDICTING BIODIESEL PROPERTIES

ML has been utilized not only to predict biodiesel yield but also to estimate several properties of biodiesel, such as Cetane number (CN), density, viscosity, flash point, pour point, cloud point, and CSC, which are used to determine fuel quality according to standardized methods like ASTM D6751 and EN 14214. However, measuring these properties through experimental procedures is time-consuming, expensive, and prone to error. Thus, precise models for approximating biodiesel physicochemical properties from its chemical and physical features are crucial for

the scientific community. The minimum CN values required for petrodiesel fuel according to ASTM D975 and EN 590 are 40 and 51, respectively, whereas the minimum CN values for biodiesel according to ASTM D6751 and EN 14214 are 47 and 51, respectively. The CN of biodiesel depends on various factors, including feedstock growth conditions, oil processing technology, and transesterification method, and can range from 48 to 67. CN is an essential metric to measure the ignition and combustion quality of diesel fuels. Ramadhasa et al. (2006) [29] developed accurate ANN models to predict the CN of biodiesel. Similarly, Cheenkachorn (2014) [30] found that the MLPNN model could better estimate the CN of biodiesel than the MLR model, and Giwa et al. (2015) [31] found that the FAME profile-based MLPNN model could estimate the CN of biodiesel. De Oliveira et al. (2017) [32] used an intelligent GA-based BPNN model to predict the properties of biodiesel fuels according to FAME compositions. Hosseinpour et al. (2016) [33] demonstrated that the MLPNN-PLS model was more robust than the classical PLS method in generalizing the CN of biodiesel.

Vegetable oil and waste cooking oil have high viscosity, which is one of the properties used to distinguish oil and biodiesel. Therefore, reducing viscosity is a top priority. ASTM D6751 and EN 14214 norms prescribe a biodiesel viscosity range of 1.9-6.0 mm²/s and 3.5-5.0 mm²/s, respectively (measured at 40°C) [33]. Giwa et al. (2015) [31] reported that a FAME profile-based MLPNN model could adequately model the Kinematic Viscosity (KV) of biodiesel. Cheenkachorn (2014) [30] claimed that the accuracy of the MLPNN model trained based on the FAME profile was comparable to the established mathematical equation in estimating the KV of biodiesel. In a similar study, Razavi et al. (2018) [34] developed a PSO-LSSVM model based on temperature, carbon number, and double bond number, which precisely predicted the KV of biodiesel compared to the ANFIS model developed by Mostafaei (2018) [35]. Hosseini et al. (2019) [36] compared the accuracy of the MLPNN model with the previously developed semi-theoretical approach in estimating the DV of fatty acid esters and biodiesels. The MLPNN model developed based on pressure, temperature, Pseudo critical density, and molecular mass was more precise than the semi-theoretical model. Aminian and Zarenezhad (2018) [37] compared the prediction capability of five soft computing approaches, including the SVM, ANFIS, MLPNN, GA-MLPNN, and SA-MLPNN approaches, for generalizing the KV of diesel/biodiesel blends in terms of biodiesel

content, temperature, carbon atom number, and double bond number. The ANFIS model was the most accurate choice. Similar studies were conducted to predict other properties such as density, flash point, cloud point, etc. using ANFIS models [38-44], which also demonstrated their superiority. Hence, it can be inferred that ANFIS models are the way to go forward.

CHAPTER 3

AIM AND SCOPE OF PRESENT INVESTIGATION

3.1. EXISTING METHODOLOGY

As stated earlier, the use of machine learning (ML) techniques has not yet been explored in the prediction of washing and wash water related properties. Despite an in-depth review paper by Aghbashlo et al. (2021) [14], which covers a wide range of topics in biodiesel production, the washing stage has been neglected, leaving a significant gap in the literature. Therefore, there is a vast potential for future research to be conducted in this field. By leveraging the power of suitable machine learning algorithms, it is possible to predict the number of wash cycles required based on the properties of waste cooking oil (WCO) samples, wash water, or the intermediate product. This prediction mechanism can also be used as a selection criterion to determine whether the use of a specific WCO and washing water would be economically and environmentally viable, by considering factors such as cost, efficiency, and sustainability. Such an ML-based approach would not only optimize the washing process but also help in the development of efficient and sustainable biodiesel production practices. Therefore, further research in this area is warranted to exploit the full potential of machine learning in biodiesel production.

3.2 PROPOSED METHODOLOGY

An adaptive neuro-fuzzy inference system (ANFIS) is a powerful tool that integrates both neural networks and fuzzy logic principles in a single framework. It is a type of artificial neural network that is based on Takagi-Sugeno fuzzy inference system, and it has the potential to capture the benefits of both approaches. ANFIS has an inference system that corresponds to a set of fuzzy IF-THEN rules, which have learning capability to approximate nonlinear functions. This makes ANFIS a universal estimator that can be used in a wide range of applications. To use ANFIS in a more efficient and optimal way, one can use the best parameters obtained by a genetic algorithm. This can improve the accuracy and reliability of the ANFIS model, making it more effective for making predictions. Since there has been no previous attempt at modeling wash water in machine learning, the relatively straightforward ANFIS technique has been employed. The

ANFIS model takes in experimental data as input and makes a prediction of the expected number of wash cycles. This prediction is compared and correlated with the actual experimental output value for the respective input values. Depending on the difference in the value, the ANFIS parameters are tweaked and adjusted to make a better prediction. This process is repeated until the model has been satisfactorily trained and can accurately predict the expected number of wash cycles based on the input parameters. With the use of ANFIS, it is possible to make more informed decisions about the viability of using a particular sample of waste cooking oil and washing water, both economically and environmentally.

3.3 ADVANTAGES OF PROPOSED METHODOLOGY

The ANFIS model is widely recognized as one of the most efficient and quick models available in the field of machine learning. The ANFIS model is unique in that it combines both numerical and linguistic knowledge, allowing it to make more informed decisions when classifying data and identifying patterns. This makes it a particularly powerful tool when it comes to predicting the number of wash cycles required for a given WCO sample or intermediate product. In comparison to other models such as artificial neural networks (ANN), the ANFIS model is more transparent to the user and causes fewer memorization errors. This is due to the fact that the ANFIS model has a simpler structure, making it easier to interpret and understand how it arrived at a particular prediction. Moreover, the ANFIS model has the ability to adapt and learn quickly, which is a key advantage when it comes to predicting wash cycles. This means that it can adjust its parameters based on new data inputs and improve its accuracy over time. Another advantage of the ANFIS model is its nonlinear ability. This means that it can capture and represent complex nonlinear relationships between input and output variables, making it particularly effective when dealing with real-world data that often involves nonlinear relationships. Finally, the ANFIS model is also very cost and time-efficient, which is particularly important in industries where time and resources are at a premium. With all these advantages, it is clear why the ANFIS model is the ideal mechanism for training a model to predict wash cycles in the context of WCO and intermediate products.

3.4 CONSTRAINTS

One of the major challenges in using machine learning (ML) techniques for predicting washing and wash water related properties is the lack of studies and data available in this field. Machine learning models require large amounts of data to efficiently train and accurately predict outcomes. Unfortunately, in the case of wash water related properties, there is a dearth of data available. This constraint makes it challenging to develop a robust and accurate model that can predict the expected number of wash cycles. Given this constraint, physically determining the properties is an unavoidable task. While it is possible to use existing data to train a machine learning model, the lack of data means that the model may not be accurate enough to make reliable predictions. Furthermore, while the adaptive neuro-fuzzy inference system (ANFIS) is a relatively straightforward machine learning technique, it still requires a certain level of expertise to use and interpret the results. Despite these limitations, the ANFIS model is a highly efficient and cost-effective machine learning technique that has the ability to learn and adapt to new data inputs. It is particularly useful for capturing and integrating both numerical and linguistic knowledge, making it a powerful tool for predicting washing and wash water related properties. While the model may not be 100% accurate due to the limited availability of data, it remains a valuable tool for researchers to explore and gain insights into this field.

CHAPTER 4

MATERIALS AND METHODS

4.1 Collection of waste cooking oil

Consuming food prepared with Waste Cooking Oil (WCO) can lead to several health hazards. According to Ambreen et al. (2020) [45], long-term consumption of cooking oil that is repeatedly heated can result in hepatic dysfunction. Ng et al. (2014) [46] also reported that prolonged consumption of repeatedly-heated oil can lead to an increase in blood pressure, total cholesterol, and vascular inflammation. Due to the potential health risks associated with WCO consumption and the environmental impact of its disposal, various research efforts have been initiated to recycle or repurpose WCO. The Sathyabama Institute of Science and Technology mess was a major source of WCO, generating a significant amount of WCO while cooking for approximately 12,000 people daily. Therefore, it is essential to find a suitable application for this waste product. However, it should be noted that not all WCO is suitable for making biodiesel, and the collected oil needs to be evaluated for its properties.

4.2 Measurement of Biodiesel Properties Before Washing

It was previously mentioned that not all WCOs can be efficiently converted into biodiesel. Oils that have a very high FFA, a too high or a low density, viscosity etc. is unsuitable for conversion to biodiesel because it can become a tedious process with unnecessary wastage of resources. There is also a requirement to meet the ASTM specifications, failing which there can be permanent damage to the engine.

4.2.1 FFA and Acid Value

Free fatty acids (FFA) are formed from triacylglycerol when ester bonds are cleaved due to the influence of factors such as lipase activity, high temperature, and moisture. Among the various reasons for the production of FFA during the second stage of lipid oxidation, hydrolysis of lipids is the most dominant. FFA can act as pro-oxidants in oils, thereby accelerating the rate of hydroperoxide decomposition. Consequently, oils with high FFA content can undergo further oxidation and develop unpleasant taste and flavor. Therefore, FFA content is a

critical parameter in the refining of edible oil, and it is often used to assess oil quality and its suitability for consumption. Additionally, the FFA content plays a crucial role in determining the feasibility of converting oil to biodiesel, as oils with high FFA percentage cannot be directly transesterified.

The FFA value can be determined by titrating NaOH against a mixture of 10g of the sample and 100ml ethanol in a 250ml Erlenmeyer flask with phenolphthalein indicator until a light pink color is achieved. Ideally, the observed FFA value should be under 4%, although values up to 10% can be acceptable. For the research conducted, all the samples collected had $\text{FFA}\% < 5\%$. The acid value can be calculated by multiplying the $\text{FFA}\%$ by 2.

4.2.2 Density and Viscosity

The relationship between density and viscosity is an important consideration in the production of biodiesel from waste cooking oil. WCO often contains impurities such as water, free fatty acids, and other contaminants that can affect the density and viscosity of the oil. In general, waste cooking oil with a higher density tends to have a higher viscosity, which can make it more difficult to process into biodiesel. This is because high viscosity can lead to increased friction and resistance within the processing equipment, which can reduce the efficiency of the production process. To overcome this issue, the waste cooking oil may need to be treated or pre-processed to remove impurities and reduce its viscosity. Similarly, the relationship between viscosity and density can also have an impact on the properties of the final biodiesel product. Biodiesel produced from waste cooking oil with a higher density and viscosity may have a higher cloud point, which is the temperature at which the fuel begins to solidify or become cloudy. This can limit the use of the biodiesel in colder temperatures, which can be a disadvantage in certain applications. Therefore, it is important to carefully consider the density and viscosity of waste cooking oil feedstocks when selecting them for biodiesel production. Pre-processing and treatment methods can be used to improve the properties of the feedstock and reduce its viscosity, which can improve the efficiency and quality of the biodiesel production process. By selecting high-quality feedstocks and optimizing the processing parameters, it is possible to produce high-quality biodiesel that meets the necessary specifications for various applications. Density is a crucial factor in the movement of diesel within an engine,

and it must be below 0.9 for petrodiesel. The similarity in properties between waste cooking oil (WCO) and petrodiesel led to the idea of using WCO as a feedstock for biodiesel. Rudolf Diesel himself tested vegetable oil as fuel for his engine, but the widespread availability and ignorance of the environmental impact of petroleum at the time meant that it was not considered. However, even after conversion to biodiesel, the density of raw oil is still too high to be utilized by an engine, requiring a blend with a small proportion of petrodiesel. The biodiesel to petrodiesel ratio can vary, but the most commonly used blend is B6, consisting of 6-20% petrodiesel. Another common blend is B5, which contains 95% biodiesel. Viscosity is another important property that affects the flow of biodiesel in an engine. Highly viscous liquids can impede smooth flow, so it is critical to ensure that the viscosity falls within the ideal range. For petrodiesel, the expected viscosity is around 3.60, while for biodiesel, it can be as high as 5.90.

4.2.3 Moisture Content

Moisture content is a critical parameter to consider in biodiesel production and use, as it can have a significant impact on the quality and stability of the fuel. The presence of water in biodiesel can cause several issues such as microbial growth, corrosion, and engine damage. Biodiesel is hygroscopic, meaning it has a strong affinity for water and can absorb moisture from the surrounding environment. Moisture content refers to the amount of water present in biodiesel, which distinguishes it from petrodiesel. The recommended moisture content in biodiesel is typically less than 0.10%wt, which is much lower than that of diesel fuel. High moisture content in biodiesel can lead to several problems during handling, storage, and transportation. For example, water accumulation can cause microbial growth in fuel handling equipment and storage tanks, leading to clogging, fouling, and corrosion of metal components. Microbial growth can also lead to the formation of sediment and sludge, which can reduce the quality and performance of the fuel. Furthermore, the presence of free water in biodiesel and diesel fuel can encourage biological growth in storage tanks, leading to the corrosion of metals. Corrosion can damage the fuel storage and transportation equipment, resulting in increased maintenance costs and potential safety hazards. To prevent these issues, it is crucial to minimize the moisture content in biodiesel. This can be achieved by using high-quality feedstocks, optimizing the production process to

reduce water content, and storing the fuel in dry, clean, and airtight containers. Additionally, regular inspection and maintenance of fuel handling and storage equipment can help to prevent microbial growth and corrosion. By minimizing moisture content, it is possible to produce and use high-quality biodiesel with improved performance and durability.

4.3 Transesterification

In this experiment, waste cooking oil (WCO) was collected daily over a period of 20 days from the mess hall facility at Sathyabama Institute of Science and Technology in Tamil Nadu, India. The WCO was collected in a clean, dry container to prevent contamination. After determining the FFA content, the WCO was transesterified using a 1:3 molar ratio of methanol to WCO, with NaOH as a catalyst. Transesterification is a chemical reaction that converts the WCO into biodiesel by reacting it with methanol and a catalyst, such as NaOH or potassium hydroxide (KOH). The transesterification reaction was carried out for a period of 90 minutes at the same institute in Chennai, under controlled conditions such as temperature, pressure, and stirring rate. The reaction mixture was allowed to settle for 8 hours at room temperature to separate the resulting biodiesel from the byproduct, crude glycerol. Crude glycerol is a byproduct of the transesterification process and contains impurities such as water, methanol, and catalysts. The separation of biodiesel from crude glycerol is a critical step in the biodiesel production process, as it determines the purity and quality of the final product. Overall, this experiment demonstrates the production of biodiesel from WCO using a simple and efficient transesterification process. The use of waste cooking oil as a feedstock for biodiesel production has several advantages, including reducing environmental pollution and promoting sustainable development. Essentially the reaction can be summed up as:





Fig 4.1. Transesterification set up

4.4 Washing and wash water collection

After transesterification of waste cooking oil (WCO) to produce biodiesel, washing is an important step to remove any impurities that may have been carried over from the transesterification process. The biodiesel underwent wet washing as described in Ranjan et al. (2018) [47]. In this experiment, the washed biodiesel was left to settle at the top due to its density difference. The pH of the collected wash water was tested using a pH meter or pH paper to determine the acidity or basicity of the water. The washing process was repeated until the pH became neutral, which indicated that all the acid and base impurities had been removed. The number of washing cycles needed varied from 2 to 5, depending on the quality of the WCO used. The wash water was collected and analyzed for properties such as turbidity, pH, and alkalinity, to determine the effectiveness of the washing process. Turbidity refers to the cloudiness or haziness of the water caused by suspended particles, and it is an indicator of the number of impurities removed. It can be measured using a turbidimeter or nephelometer. For this study we used a turbidimeter, which uses a light source, typically a LED or a tungsten

filament lamp, to shine a beam of light through the sample, Omar et.al. (2009) [48]. The amount of light that passes through the sample is then measured by a photodetector. The amount of light that is scattered or absorbed by the suspended particles in the sample causes the reduction in the amount of light that passes through the sample, and this reduction is then used to calculate the turbidity of the sample. pH, which is measured using a probe, and alkalinity are important parameters to measure because they can affect the quality of the biodiesel and its stability during storage. Alkalinity is measured by titration where a known volume of the water sample is treated with a standardized acid solution until the alkalinity is completely neutralized. This is usually done using a pH indicator such as phenolphthalein, which changes color at a certain pH. The endpoint of the titration is reached when the pH indicator changes color, indicating that all of the alkalinity has been neutralized. The amount of acid used in the titration is then used to calculate the alkalinity of the water sample. TSS stands for Total Suspended Solids, which refers to the dry weight of suspended particles (inorganic and organic) that can be trapped by a filter. It is a measure of the amount of solid material present in water that is not dissolved. TSS can affect water quality and can be a useful indicator of water pollution. The measurement of TSS involves filtering a known volume of water through a pre-weighed filter, drying the filter to constant weight, and weighing the filter again to determine the weight of the suspended solids. The difference between the initial and final weight of the filter gives the weight of the suspended solids, which is then expressed in mg/L or ppm. Total Oil and grease or ToG refer to the oil and grease in the water sample which is also measured in a somewhat similar fashion. The method involves extraction of oil and grease from the water sample using a nonpolar solvent, followed by evaporation of the solvent and weighing of the residue. TDS or Total Dissolved Solids as the name suggests refers to the quantity of dissolved solids in the sample. This is measured easily using a probe. The results of the analysis were recorded in a table to keep track of the washing process and to ensure that the biodiesel met the required quality standards.

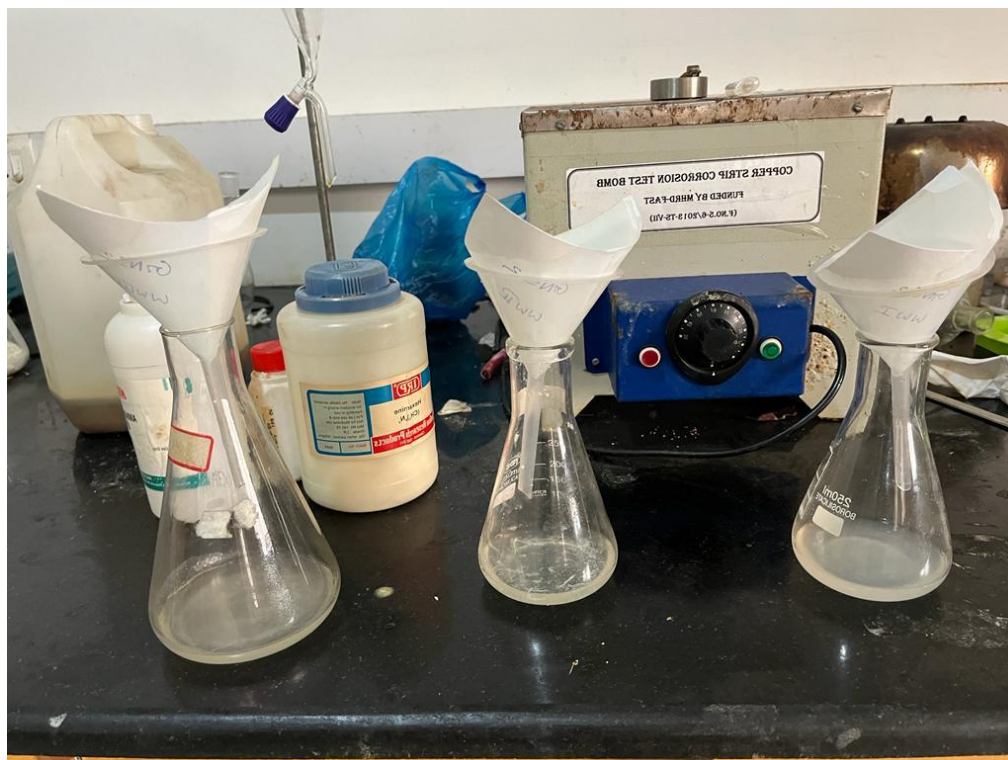


Fig 4.2. Filtering the wash water to measure Total Soluble Solids

4.5 Machine Learning Model for prediction

In this study, the ANFIS algorithm was used to predict the properties of biodiesel based on the raw oil and wash water data. ANFIS stands for Adaptive Neuro-Fuzzy Inference System, and it is a type of machine learning algorithm that combines the strengths of fuzzy logic and neural networks [50]. The ANFIS model was created using MATLAB, a powerful programming language commonly used in engineering and scientific applications. In this study, a Sugeno model was chosen, which is a type of fuzzy logic model that uses if-then rules to make predictions. The Sugeno model is particularly suitable for this application because it does not require the explicit programming of membership functions. The ANFIS model was first trained using a dataset consisting of 20 samples. The training dataset contained raw oil and wash water data, which were used to develop the prediction rules. Once the model was trained, a test dataset was loaded to evaluate the accuracy of the model. The test dataset consisted of a mix of samples from the training set as well as some new values. This is represented in Fig 4.3.. The `evalfis()` command was used to load the dataset on which the prediction was going to be made, and the ANFIS model was applied to make accurate predictions

based on the rules learned from the training data. If the model was satisfactory, the rules were saved on the computer, allowing for the ANFIS model to make predictions on new data. Overall, the ANFIS algorithm proved to be an effective tool for predicting the properties of biodiesel based on raw oil and wash water data.

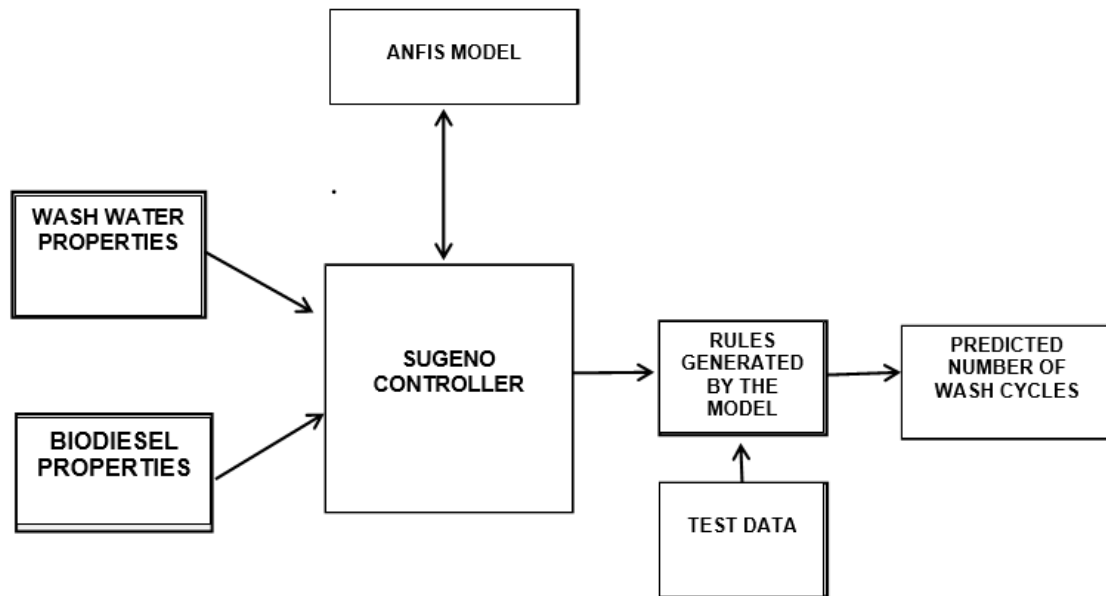


Fig 4.3. Proposed Adaptive Neuro Fuzzy Optimization Model

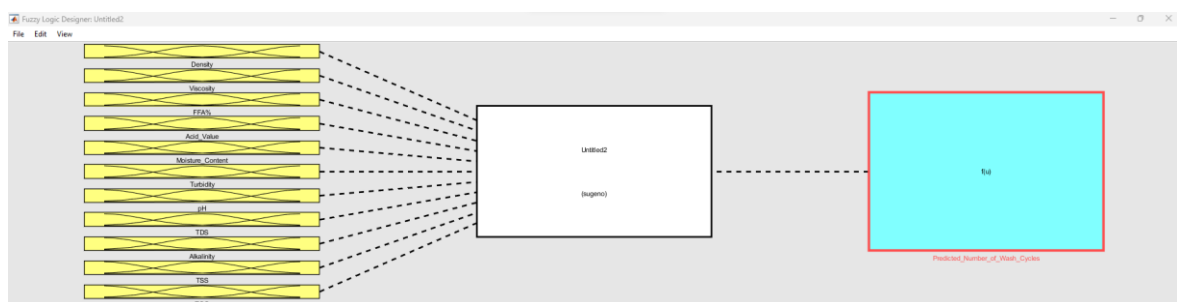


Fig 4.4. Implementation of the model in MATLAB

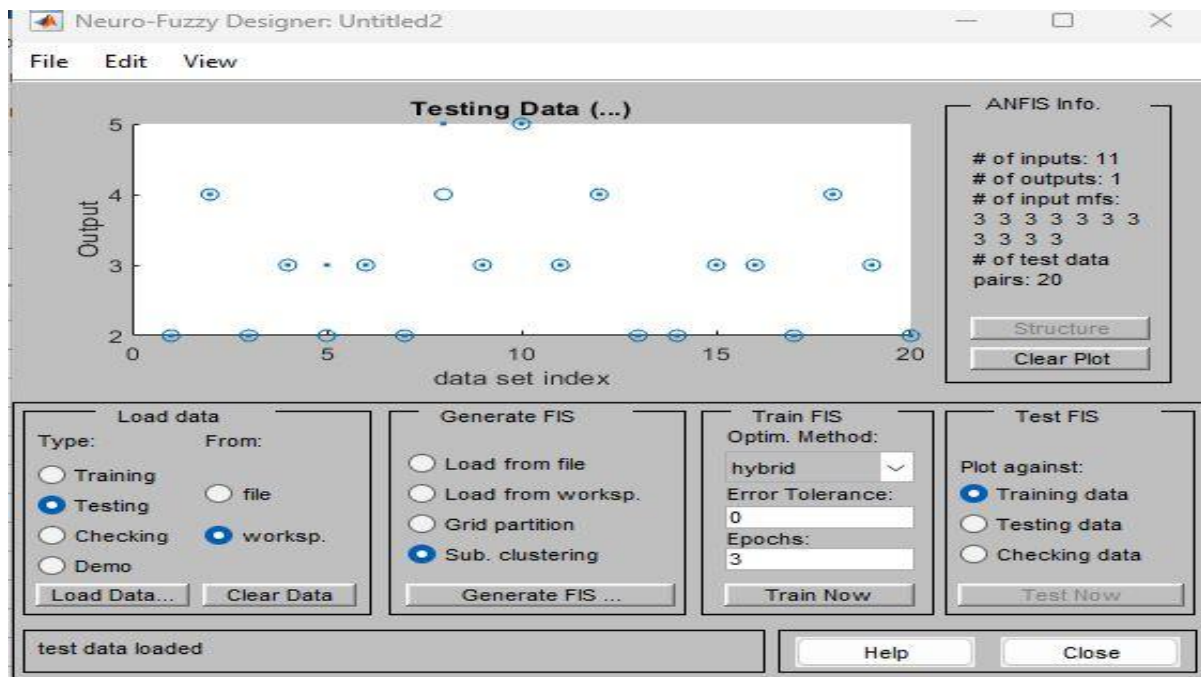


Fig 4.5. The training and testing data is loaded

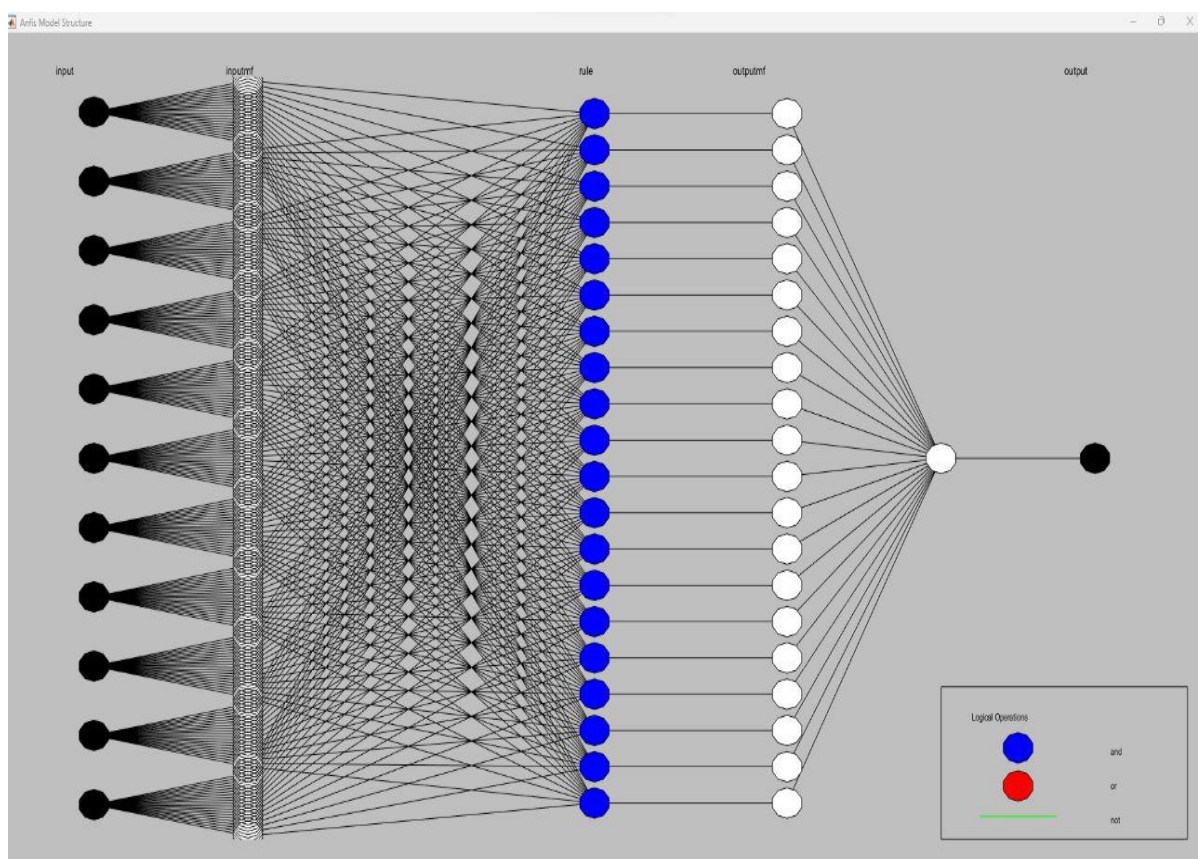


Fig 4.6. The Generated ANFIS Architecture

The adaptive neural network architecture for the fuzzy inference system is

illustrated in Figure 4.6. The input layer comprises 11 neurons that represent both biodiesel properties and wash water characteristics. Each input neuron has five input membership functions that are linked to the corresponding functions of other neurons. Through this approach, the network has formulated all possible combinations (20 rules as seen in fig 4.7.) and generated 20 output membership functions that are linked to a single output neuron. The network employs "AND" logic for rule formulation.

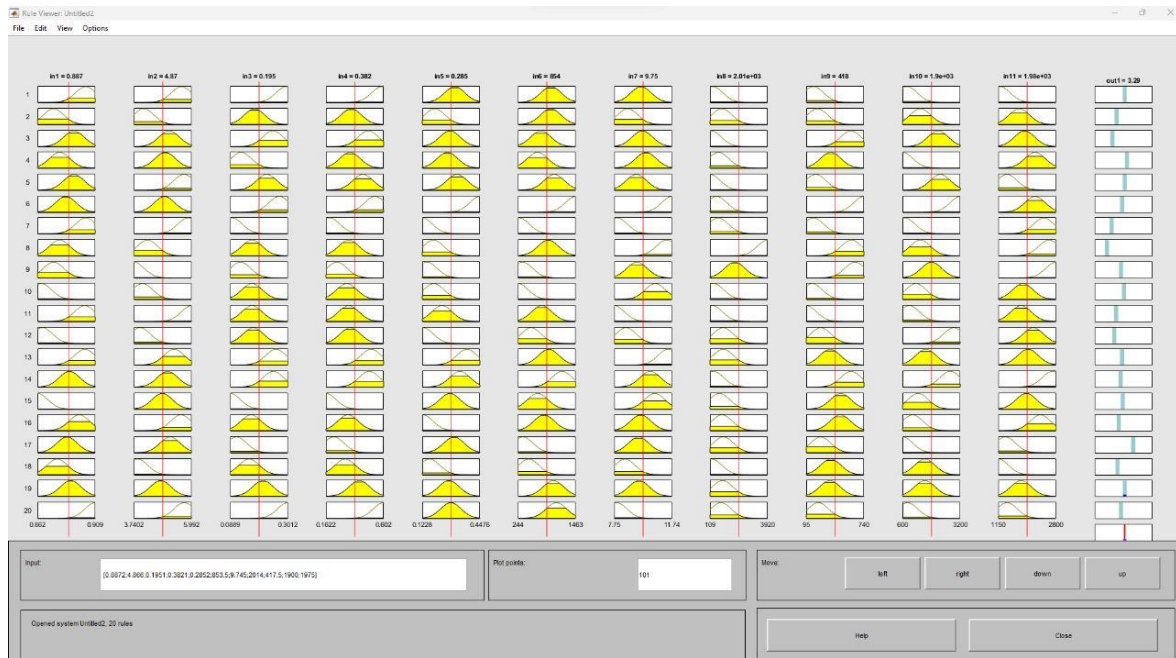


Fig 4.7. The 20 Rules that were generated by the ANFIS Algorithm

4.5.1. Membership Function and Linguistic variables for Inputs

A total of 11 inputs are chosen for the system. Including the various Biodiesel and Wash water properties. The membership function contains three assigned linguistic variables and is triangular. Figure 4.8 displays the process of fuzzification using the triangular membership function. For defuzzification, the weighted average method is employed.

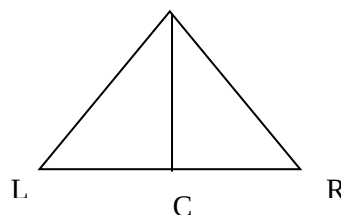


Figure 4.8. Triangular membership functions

The degree of membership function is given by the following equation:

$$\mu_{triang}(x) = \begin{cases} 0, & x < L \\ 1 - \frac{|c-x|}{(R-L|2)}, & L < x < R \\ 0, & x > R \end{cases}$$

Where, $\mu_{triang}(x)$ is the degree of membership function for a triangular fuzzy set on the universe of discourse x.

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CHAPTER 5

RESULTS AND DISCUSSION

5.1 Evaluation of Biodiesel properties

The collected data from the experiments has been carefully recorded and organized in a comprehensive manner, allowing for easy interpretation and analysis. One notable finding was the interrelation between certain properties, particularly the direct proportionality observed between density and viscosity in most of the cases. The data showed that as the density of oil increased, so did its viscosity. However, upon closer examination of the data, it was discovered that there was no apparent correlation between any of the properties and the number of washing cycles. The data showed some inconsistencies and irregularities that were difficult to explain. For instance, while moisture content and turbidity appeared to be moderately correlated in some samples, this relationship was not consistent across all of the data. Nonetheless, despite these challenges, the data was deemed suitable for use in an ANFIS model, which was used for training and testing. By leveraging the ANFIS model, it was hoped that the complex relationships between the various properties could be better understood, even in the absence of a clear correlation with washing cycles.

5.1.1 FFA % and Acid Value

The experimental analysis of the collected samples has shown that all of the samples fall within the ideal range for both Free Fatty Acid (FFA%) and Acid Value. This is significant because it indicates that the oil samples have good quality and purity, and do not require any intermediate steps prior to transesterification. In other words, the samples can be directly converted into biodiesel, without the need for further processing. This is a valuable finding because intermediate steps such as degumming, neutralization, and bleaching can add additional time, cost, and complexity to the biodiesel production process. By eliminating the need for these steps, the overall production time and cost can be significantly reduced, while also simplifying the overall process. This discovery highlights the importance of careful sampling and analysis in the biodiesel production process, as it allows for the identification of high-quality oil sources that can be more efficiently converted into biodiesel.

Table 5.1. FFA% and Acid value of the impure biodiesel before washing

Oil Sample number	FFA%	Acid Value
Sample 1	0.16886	0.33603
Sample 2	0.22336	0.44449
Sample 3	0.16920	0.33670
Sample 4	0.11190	0.22269
Sample 5	0.17849	0.35519
Sample 6	0.20956	0.41702
Sample 7	0.09586	0.19064
Sample 8	0.24762	0.49276
Sample 9	0.16594	0.33022
Sample 10	0.26915	0.53560
Sample 11	0.17370	0.34760
Sample 12	0.12680	0.24640
Sample 13	0.30120	0.60200
Sample 14	0.29496	0.58748

Sample 15	0.08890	0.16220
Sample 16	0.25744	0.50719
Sample 17	0.24620	0.48530
Sample 18	0.12900	0.34560
Sample 19	0.16939	0.32067
Sample 20	0.15850	0.30888

5.1.2 Density and Viscosity

Being two of the most important properties that determine the suitability of the given oil sample for biodiesel production, it is critical to select only those samples that fall in the range. All the analyzed samples satisfied the required criteria to be used as biodiesel.

Table 5.2. Density and viscosity of the impure biodiesel before washing

Oil Sample number	Density(g/ml)	Viscosity(cSt)
Sample 1	0.9004	5.9920
Sample 2	0.8916	5.6980
Sample 3	0.8800	4.2700
Sample 4	0.8860	5.1520

Sample 5	0.8750	4.1220
Sample 6	0.8890	4.7890
Sample 7	0.9012	5.8500
Sample 8	0.8880	5.0560
Sample 9	0.8960	5.5740
Sample 10	0.8850	4.9340
Sample 11	0.8660	3.9836
Sample 12	0.8750	3.7402
Sample 13	0.9090	5.7032
Sample 14	0.9012	5.5960
Sample 15	0.8780	4.8472
Sample 16	0.9004	5.3096
Sample 17	0.8916	5.1187
Sample 18	0.8800	4.9618
Sample 19	0.8650	4.0762
Sample 20	0.8620	3.8829

5.1.3 Moisture content

In the study, it was found that the moisture content in most of the collected samples was higher than the ideal range, which could cause issues in the biodiesel production process. To address this, intermediate steps were needed to reduce the moisture content of the collected waste cooking oil (WCO) before transesterification. There are several methods available to reduce the moisture content in WCO, including heating, vacuum distillation, and centrifugation. Overall, reducing the moisture content of WCO is crucial to ensure the quality of the final biodiesel product. By using appropriate intermediate steps to reduce moisture content, it is possible to produce biodiesel with optimal properties and avoid issues during storage and transportation.

Table 5.3. Moisture content of the impure biodiesel before washing

Oil Sample number	Moisture content (%)
Sample 1	0.2338
Sample 2	0.3185
Sample 3	0.1856
Sample 4	0.3013
Sample 5	0.1934
Sample 6	0.2730
Sample 7	0.1227
Sample 8	0.3349

Sample 9	0.1267
Sample 10	0.4475
Sample 11	0.1278
Sample 12	0.1489
Sample 13	0.2840
Sample 14	0.3064
Sample 15	0.2786
Sample 16	0.3749
Sample 17	0.2787
Sample 18	0.2645
Sample 19	0.1879
Sample 20	0.1645

5.2 Biodiesel yield

The yield of biodiesel obtained was found to be greater than 90% in the majority of cases, indicating that the transesterification process was highly efficient. Furthermore, the properties of the resulting biodiesel were in accordance with the standards set by ASTM and DSTN, indicating that the biodiesel was of high quality and suitable for use as a fuel. The high yield and quality of the biodiesel produced from the waste cooking oil suggests that it is a viable source for biodiesel production, which can help in the development of a sustainable energy source.



Fig 5.1. Separation of biodiesel and glycerol (Soap)



Fig 5.2. Final Biodiesel product

Table 5.4. Biodiesel yield for the oil samples

Oil Sample number	Biodiesel yield (%)
Sample 1	93
Sample 2	95
Sample 3	83
Sample 4	94
Sample 5	98
Sample 6	91
Sample 7	89
Sample 8	94
Sample 9	96
Sample 10	92
Sample 11	91
Sample 12	92
Sample 13	94
Sample 14	87
Sample 15	97

Sample 16	91
Sample 17	93
Sample 18	92
Sample 19	94
Sample 20	92

5.3 Wash water characteristics

The measured values of different wash water characteristics were tabulated and compared to determine any potential correlations. However, the study found no clear correlation between these properties and the number of wash cycles. Despite this, the study did find that turbidity showed the most promise as an indicator of the number of wash cycles required. It was observed that in most cases, a high turbidity meant that more washing was necessary to achieve desired results. The production of biodiesel comprises several stages, starting from the extraction of oil from the raw materials to the conversion of the oil into biodiesel. However, each of these stages can potentially introduce impurities into the final product, which may need further washing to eliminate. Hence, the effectiveness of washing may be influenced by several factors, including the quality of raw materials, the efficiency of the conversion process, and the effectiveness of the washing process. It is worth noting that these factors can interact in complex ways, making the optimization of washing processes a challenging task in biodiesel production. Further research is needed to fully understand the complex interplay of factors that influence the effectiveness of washing in the production of biodiesel.

Table 5.5. Properties of the wash water after one round of washing the biodiesel

Oil Sample number	Turbidity	pH	TDS	Alkalinity	TSS	ToG
Sample 1	746	7.75	260	95	900	1800
Sample 2	1012	9.28	109	200	2300	1400
Sample 3	884	11.36	3920	600	1400	2600
Sample 4	348	9.43	990	255	600	1350
Sample 5	936	8.68	890	220	1400	1750
Sample 6	994	9.46	940	360	1600	1800
Sample 7	268	7.95	664	175	700	2450
Sample 8	1177	10.24	340	595	2750	2700
Sample 9	796	9.58	908	475	1050	2350
Sample 10	1463	11.74	542	740	3200	2200
Sample 11	520	8.56	974	257	2900	2150
Sample 12	340	9.32	1750	640	1900	2800
Sample 13	1055	7.91	837	230	820	1400
Sample 14	943	9.60	290	176	800	1200

Sample 15	662	10.55	736	480	1300	1950
Sample 16	894	11.48	990	362	1650	2000
Sample 17	729	9.69	180	593	2200	1900
Sample 18	658	9.94	670	368	600	2200
Sample 19	244	10.59	343	160	1200	1850
Sample 20	471	8.48	220	369	1600	1150

5.4 Performance analysis of the Model

Table 5.6 Performance Analysis of the ANFIS Model for predicting the number of wash cycles

Oil Sample number	ANFIS Model predicted number of wash cycles	Actual number of wash cycles	Error
Sample 1	2.0339	2	-0.01695
Sample 2	3.9491	4	0.02545
Sample 3	4.4906	4	-0.12265
Sample 4	2.9790	3	0.007
Sample 5	2.3646	2	-0.1823

Sample 6	3.0021	3	-0.0007
Sample 7	2.0064	2	-0.0032
Sample 8	3.9657	4	0.008575
Sample 9	2.9828	3	0.005733

AVERAGE ERROR = -0.0278502

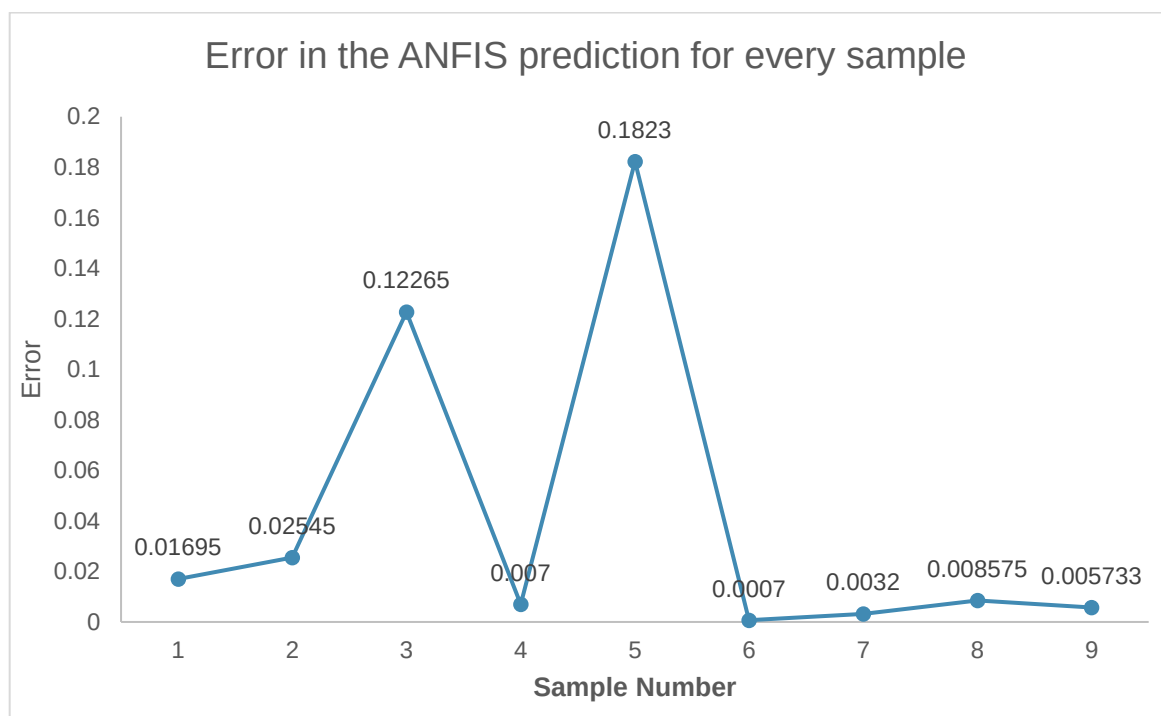


Fig 5.3. Error of the Predicted value from the observed number of wash cycles.

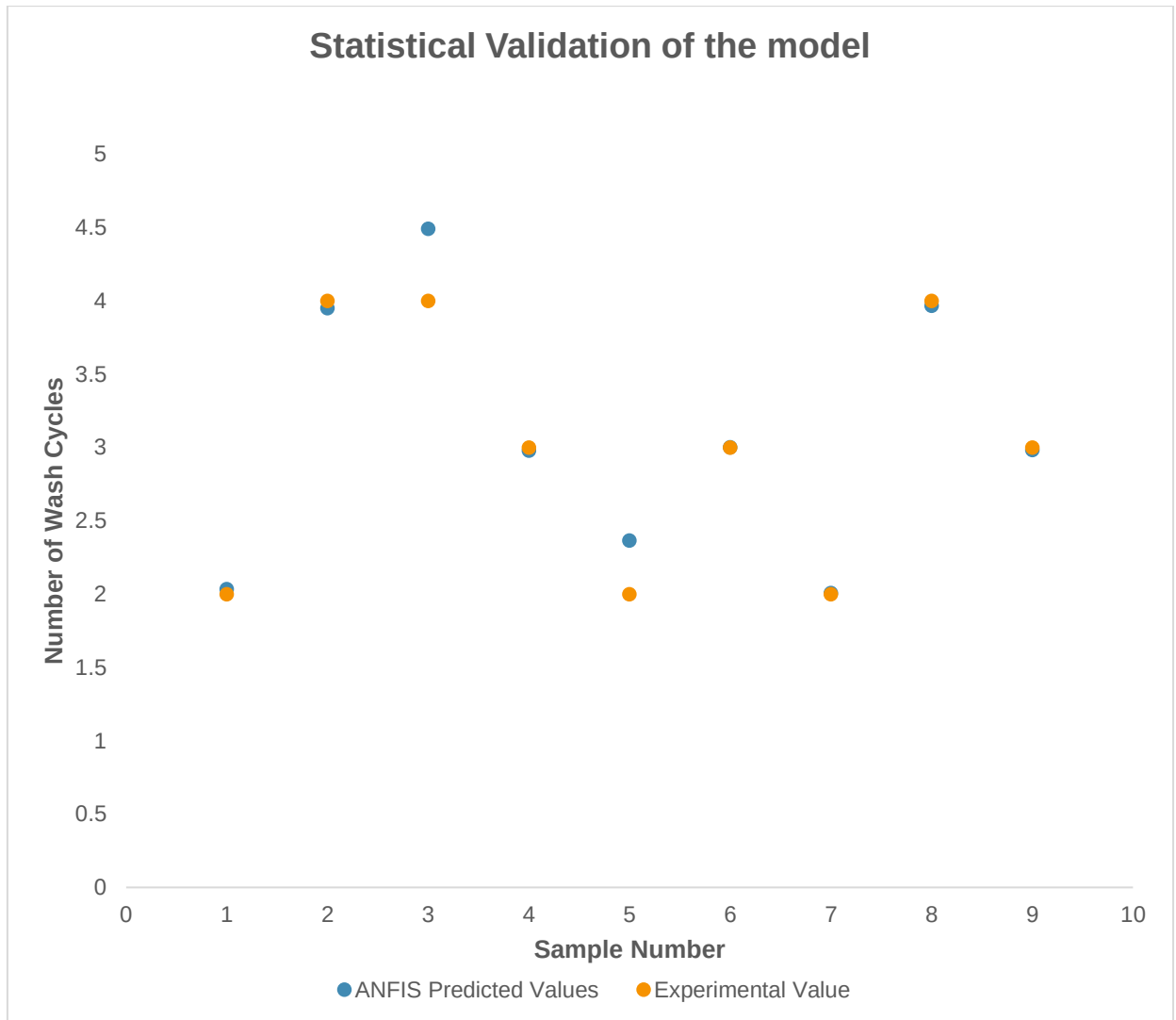


Fig 5.4. Statistical Validation of the ANFIS model by plotting the deviation of the predicted value from the experimental value for every sample.

Table 5.6 presents a comparison between the model-generated results and observed values during the production process. It's worth noting that the machine learning (ML) model produced decimal values that needed to be rounded to the nearest whole number to obtain expected values. This is a common issue with ML models, which often output decimal values that require processing to become more usable. Overall, the training conducted using data from the 20 samples was insufficient to capture all the system's nuances, but it was sufficient to provide accurate predictions. Further research and data collection could enhance the accuracy and reliability of the ANFIS model. Nevertheless, this study demonstrated that the model was a useful tool for predicting the number of washing cycles necessary to remove impurities from biodiesel.

The results demonstrate a high level of accuracy in the predictions as shown in figures 5.3. and 5.4., with only two cases deviating slightly from the expected outcome. In the vast majority of instances, the predictions were remarkably close to the actual outcomes, indicating the efficacy of the modelling approach used.

This level of accuracy is a significant achievement, especially when considering the complexity and variability of the systems being modelled. It suggests that the model is robust and capable of handling a wide range of inputs and conditions, making it a valuable tool for decision-making and process optimization.

While the two cases that deviated slightly from the expected outcome may be seen as less accurate, it is important to note that these predictions were still correct, albeit with a slightly lower degree of precision. This highlights the inherent uncertainty and variability in many real-world systems and reinforces the importance of accounting for these factors in modelling and analysis.

CHAPTER 6: CONCLUSION

6.1 Summary and Conclusion

The main outcome of this study was that no single parameter could be identified as having a significant impact on the number of wash cycles required. Minimizing the amount of wash water generated would be helpful, so it would be beneficial to know in advance the number of wash cycles required. This is what the study aimed to achieve. Although no definitive conclusion was reached regarding whether the properties of the oil or the wash water from the first wash influenced the outcome, the model proved to be accurate in almost all of the test runs. It should be noted that the study did not account for various impurities that may have been added at different stages of the process. However, it can be concluded that the ANFIS algorithm is an excellent choice for situations where the weight of various parameters is unknown. The algorithm proved to be highly efficient in accurately predicting the number of wash cycles required. The average error came to be approximately around ± 0.028 which proves the efficiency.

6.2 Future Scope

The process of washing biodiesel to remove impurities generates a significant amount of waste water, which can have a negative environmental impact if not handled properly. To mitigate this impact, it is important to minimize the amount of waste water generated during the washing process, or to find ways to repurpose or treat the water to reduce its impact. This idea can be implemented using other machine learning algorithms, such as MLPNN (multi-layer perceptron neural network) and RSM (response surface methodology).

Ideally, a predictor model that uses only the oil properties to accurately predict the number of wash cycles required would be incredibly useful in the real world. This model could significantly reduce the number of resources wasted on biodiesel preparation. Such a predictor model would not only be environmentally friendly but also economically beneficial, as it would reduce the costs associated with preparing biodiesel. By leveraging the power of machine learning algorithms, researchers can develop innovative solutions to the challenges facing the

biodiesel industry and move towards a more sustainable future.

6.3 Limitations of present Study

During the course of the research, two significant limitations were encountered. The first limitation was related to the scarcity of available research data on washing in the biodiesel industry. As a result, the research team had to conduct physical experiments to gather the necessary data for the study. However, due to the time and resource constraints, the team was only able to collect around 20 new samples. While the model proved to be accurate in test runs, more testing is required to ensure the reliability and effectiveness of the algorithm.

The second limitation was related to the difficulty in establishing a clear relationship between a single property and the amount of washing required. While turbidity and FFA (free fatty acids) showed promising results, the study could not conclusively establish a direct correlation between any single property and the amount of washing required. More experimental data is needed to better understand the complex interactions between the various properties of biodiesel and the washing process.

Despite these limitations, the research represents an important step forward in understanding and optimizing the washing process in the biodiesel industry. By leveraging advanced machine learning algorithms and carefully designed experiments, the study highlights the potential for innovative solutions to the challenges facing the industry. Moving forward, it will be important to continue gathering data and refining the models to further improve the efficiency and sustainability of biodiesel production.

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