INTEGRATING TAGUCHI METHOD AND ARTIFICIAL NEURAL NETWORK (ANN) FOR IMPROVING NON-EDIBLE BIODIESEL YIELD

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DEDICATION

I dedicate this report to all my family members, mentors, friends and the participants who contributed to this research. Their unwavering belief in my abilities, their encouragement and their constant presence have been invaluable throughout this journey. I would like to express my deepest gratitude to my supervisor, Dr. Mahanum binti Mohd Zamberi. It is through her unwavering support, guidance and invaluable expertise that I have been given the opportunity to embark on this study. Dr. Mahanum's commitment to my academic growth and her willingness to share her knowledge have been instrumental in shaping the outcome of this research. The unwavering dedication and mentorship have propelled me forward and played a crucial role in bringing this study to its completion. This dedication is a tribute to everyone profound impact on my academic journey and I am forever grateful for their unwavering support.

ABSTRACT

Hevea brasiliensis also known as rubber seed oil (RSO) and Jatropha curcas oil (JCO) are non-edible feedstock used in biodiesel production. In this study, the integration of the Taguchi Method and Artificial Neural Network (ANN) are used to maximize and predict biodiesel yield of RSO and JCO feedstock using different waste shells as catalyst via two-step transesterification microwave irradiation. The Taguchi Method is utilized to design the optimum experiments with 5 factors (catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power) at 3 levels of experiment parameters using orthogonal array (OA). The highest biodiesel yield is 96.2% achieved by combination of Perna Viridis (PV) catalyst, 12 wt.% catalyst loading, 1:9 methanol to oil molar ratio, 7 minutes of reaction time and 350 W microwave power for RSO while highest biodiesel yield is 95.26% achieved by combination of Corbicula Fluminea (CF) catalyst, 12 wt.% catalyst loading, 1:15 methanol to oil molar ratio, 9 minutes of reaction time and 400 W microwave power for JCO. Optimizations of experiment were done through SNR and ANOVA analysis to achieve the optimum combinations. ANN with single hidden layer using Levenberg-Marquardt back-propagation algorithm achieved R^2 of 0.99953 for RSO and 0.99736 for JCO indicate excellent linear regression predictions for the biodiesel yield. The high value of linear regression shows that ANN with a quick propagation algorithm is an appropriate approach for biodiesel conversion prediction.

ABSTRAK

Hevea brasiliensis yang juga dikenali sebagai minyak biji getah (RSO) dan minyak Jatropha curcas (JCO) adalah bahan suapan bukan makanan yang digunakan dalam pengeluaran biodiesel. Dalam kajian ini, integrasi Kaedah Taguchi dan Rangkaian Neural Buatan (Artificial Neural Network atau ANN) digunakan untuk memaksimum dan menjangkakan hasil biodiesel daripada bahan suapan RSO dan JCO dengan menggunakan cengkerang buangan yang berbeza sebagai pemangkin melalui proses transesterifikasi gelombang mikro dalam 2 langkah. Kaedah Taguchi digunakan untuk mereka bentuk 5 faktor (jenis pemangkin, suapan pemangkin, nisbah mol metanol kepada minyak, masa tindak balas dan kuasa gelombang mikro) serta 3 tahap parameter eksperimen dengan menggunakan tatasusunan ortogon. Hasil biodiesel tertinggi adalah 96.2% dicapai melalui kombinasi pemangkin Perna Viridis (PV), suapan pemangkin 12 wt.%, nisbah mol metanol kepada minyak 1:9, masa tindak balas 7 minit dan 350 W kuasa gelombang mikro bagi RSO manakala hasil biodiesel tertinggi adalah 95.26% dicapai melalui kombinasi pemangkin Corbicula Fluminea (CF), suapan pemangkin 12 wt.%, nisbah mol metanol kepada minyak 1:15, masa tindak balas 9 minit dan 400 W kuasa gelombang mikro bagi JCO. Pengoptimuman eksperimen telah dilakukan melalui analisis SNR dan ANOVA untuk mendapatkan kombinasi eksperimen yang terbaik. ANN dengan lapisan tersembunyi tunggal menggunakan algoritma penyebaran balik Levenberg-Marquardt mencapai nilai R^2 sebanyak 0.99953 untuk RSO dan 0.99736 untuk JCO yang menunjukkan jangkaan regresi linear yang sangat baik bagi penghasilan biodiesel. Nilai regresi linear yang tinggi menunjukkan bahawa ANN dengan algoritma penyebaran balik yang cepat adalah pendekatan yang sesuai untuk menjangkakan pemprosesan biodiesel.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
ASTM	-	American Society of Testing and Materials
CaDG	-	Calcium diglyceroxide
CaF_2	-	Fluorite
CaO	-	Calcium oxide
CEN	-	European Committee for Standardization
CFPP	-	Cold Filter Plugging Point
CI	-	Compression ignition
CO	-	Carbon monoxide
CO_2	-	Carbon dioxide
DOE	-	Design of experiment
DOF	-	Degrees of freedom
EN	-	European Standards
FAME	-	Fatty acid methyl esters
$Fe_2(SO_4)_3$	-	Iron(III) sulfate
FFA	-	Free fatty acid
GC-MS	-	Gas chromatography-mass spectrometry
GHG	-	Greenhouse gas
GO	-	Graphene oxide
HC	-	Hydrocarbon
HCl	-	Hydrochloric acid
H_2O	-	Water
H_3PO_4	-	Phosphoric acid
H_2SO_4	-	Sulfuric acid
JCO	-	*Jatropha curcas* oil
K	-	Potassium
KOH	-	Potassium hydroxide
Li	-	Lithium

MFMP	-	Marine fishmeal plant
MgO	-	Magnesium oxide
MR	-	Molar ratio
MS	-	Mean squares
MSE	-	Mean square error
MWI	-	Microwave irradiation
Na	-	Sodium
NaOH	-	Sodium hydroxide
NO	-	Nitric oxide
N_2O	-	Nitrous oxide
NO_x	-	Nitrogen oxide
RSM	-	Response surface methodology
RSO	-	Rubber seed oil
SDG	-	Sustainable Development Goals
SNR	-	Signal-to-noise ratio
SO_2	-	Sulfur dioxide
SPM	-	Spermine
SS	-	Sum of squares
SSE	-	Error sum of squares
SST	-	Total sum of squares
TM	-	Taguchi Method
UN	-	United Nations
WCO	-	Waste cooking oil
WFO	-	Waste frying oil

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CHAPTER 1

INTRODUCTION

1.1 Background

The exigency for fuels made from petroleum has sharply increased in recent years, driven by the quick tempo of industrialization and ever-growing motorization of societies worldwide. As developing countries strive to achieve economic growth and modernization, the reliance on petroleum-based fuels has become paramount for powering industries, transportation systems, and the overall energy needs of their populations. However, the availability of fuels with a petroleum basis is inherently limited. These valuable resources are found in a relatively small number of deposits scattered across the globe. Furthermore, the distribution of these deposits is highly concentrated, with a few regions holding the majority of the world's petroleum reserves.

This concentration of petroleum resources creates a complex dynamic in global energy markets. Nations lacking significant domestic petroleum reserves are compelled to heavily rely on energy importation for fulfilling the demands. This reliance on foreign sources of crude oil exposes these nations to various challenges, including vulnerabilities in energy security and foreign exchange rates. Consequently, countries without substantial petroleum resources face a dual crisis. First, they encounter an energy crisis as they grapple with the task of securing adequate and affordable supplies of petroleum-based fuels from international markets. The fluctuations in oil prices, geopolitical tensions, and supply disruptions can significantly impact their energy stability and economic development.

Diesel fuel emissions, for example nitrogen oxide (NOx), sulfur dioxide (SO_2), carbon monoxide (CO), spermine (SPM) and carbon dioxide (CO_2), hydrocarbon (HC) and nitrous

oxide (N_2O) can cause health and environmental problems. For example, the effects are irritation of lungs, respiratory infection, coughing, difficulty in breathing, eye irritation lungs diseases or damage and acid rain. Large-scale petroleum usage raises serious environmental and public health issues and this energy source is increasingly becoming unsustainable both economically and environmentally due to rising demand and volatile pricing (Hajjari et al., 2017). Hence, it is crucial to explore alternative combustibles that may be made from materials that are already present, such as alcohol, biodiesel and vegetable oils.

Biodiesel is an environmentally friendly fuel sourced from sustainable and biodegradable materials, manufactured using organic substances like oils from vegetables, fats from animals or waste cooking oil. "Sustainable development" frequently refers to compelling approaches for meeting the present fuel market demands while effectively leveraging the advantages of biological resources and conserving them for the future. Biodiesel demonstrates a robust connection with various Sustainable Development Goals (SDGs) outlined by the United Nations (UN). These encompass SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), SDG 13 (Climate Action), and SDG 15 (Life on Land) (Nazari et al., 2021).

Among all renewable fuels, biodiesel has drawn the most attention due to its molecular structure. The molecular composition of biodiesel renders it biodegradable, economically viable, environmentally friendly as a clean energy source, capable of mitigating pollution and non-toxic in nature. Additionally, the oil may be grown on waste and agricultural areas, which diminishes dependence on crude oil imports. Biodiesel contributes to the nation's economic independence. When used with diesel, biodiesel helps to mitigate greenhouse gas (GHG) emissions. Furthermore, according to experts, biodiesel reduces GHG emissions by 65%. Because it is cleaner than conventional fuels, biodiesel extends the life of a car's engine by improving its efficiency. Biodiesel can be employed in various applications, including

commercial automobiles, mining and agricultural machinery, generators, boilers and ships, apart from requiring significant modifications or improvements because it shares characteristics with conventional diesel fuel.

A data-driven approach in biodiesel production involves utilizing machine learning, Artificial Neural Networks (ANN), Taguchi Method (TM) and Response Surface Methodology (RSM) for various aspects of process optimization. Machine learning algorithms have the capability to analyze extensive datasets, enabling them to detect patterns and establish relationships within the data, optimizing feedstock selection and predicting optimal reaction conditions. RSM and the TM enable statistical analysis and experimentation to determine optimal parameters and minimize variability. ANN models can learn from data to predict biodiesel quality, yield and optimize process parameters. By leveraging these data-driven techniques, producers can enhance their decision-making, streamline efficiency, cut down on costs, and enhance the sustainability of biodiesel production.

In summary, this research aims to integrate the TM and ANN to improve non-edible biodiesel yield such as rubber seed oil (RSO) and *Jatropha curcas* oil (JCO). The TM will be applied to design experiments and process optimization in order to determine optimal combination of factors, for example, catalyst type, catalyst loading, methanol to oil molar ratio (MR), reaction time and microwave power. Then, the collected data will then be utilized to train an ANN model, which can learn the intricate correlations between input parameters and biodiesel yield. The integrated approach will enable the identification of optimal process conditions for maximizing biodiesel production and facilitate accurate predictions of yield based on various input parameters. By combining the strengths of the TM and ANN, this research seeks to enhance the efficiency and effectiveness of biodiesel production.

1.2 Problem Statement

RSO and JCO serve as second-generation non-edible feedstocks for biodiesel production, offering sustainability, wide availability and reduced environmental impact compared to first-generation feedstocks. In Malaysia, where rubber tree is prevalent and has significant plantations with unused seeds, RSO becomes a valuable biodiesel feedstock due to its inedibility and lack of competition with food production. Conversely, *Jatropha curcas* seeds, toxic and with no major applications, find purpose as biodiesel feedstock given their high oil content (up to 40% of seed weight) and viscosity range (27 to 40%). Mollusk shells like clam, mussel and oyster shells, abundant and featuring a unique composition primarily of calcium carbonate, serve as eco-friendly catalysts through calcination to produce calcium oxide (CaO). These shells, with a porous structure enhancing catalytic activity, offer a sustainable and cost-effective alternative to synthetic catalysts, contributing to waste reduction and providing renewable resources for catalytic applications.

Optimization and prediction of biodiesel yield is crucial to save time and cost and is applied in lots of biodiesel studies. There are various of optimization and prediction method such as RSM, TM and ANN. Lots of studies were done on biodiesel with these methods. Integration of these methods are studied to achieve optimal biodiesel yield. Researchers have explored the integration of various methods such as RSM, TM and ANN to enhance the accuracy and efficiency of biodiesel optimization and prediction. Currently, there is not much research related to integration of TM and ANN in enhancement and prediction of RSO and JCO yield.

1.3 Research Objective

The main aim of this research is to integrate TM and ANN for improving the yield of RSO and JCO biodiesel.

1. To optimize the reaction variables (catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power) in producing a high yield of RSO and JCO biodiesel using TM.
2. To predict the yield of RSO and JCO biodiesel using ANN with high performance in term of coefficient of determination (R^2) and mean square error (MSE).

1.4 Scope of Research

The scope of this research are as follows:

1. Identify parameters involved in producing a high yield biodiesel.
2. Optimize reaction variables (catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power) in biodiesel production through TM by using Minitab®21.4.
3. ANN modelling, training and prediction using MATLAB R2021a.

1.5 Significant of Research

The integration of TM and ANN in optimizing and estimating the yield of RSO and JCO biodiesel can have significant implications for cost, GHG emissions and waste disposal. Through the TM, the important process factors and levels that influence biodiesel yield can be determined, allowing for the identification of optimal parameter settings that maximize yield and minimize production costs. By optimizing the process, the consumption of raw materials,

energy and catalysts can be reduced, resulting in cost savings and improved economic feasibility in producing biodiesel.

Additionally, utilization of an ANN model trained on RSO and JCO biodiesel data enables accurate prediction of biodiesel yield based on input parameters. This predictive capability eliminates the need for manual experimentation and reduces the associated costs and resources required for trial-and-error approaches. By using the model to predict biodiesel yield, producers can make informed decisions, optimize production planning and minimize wasteful overproduction. Consequently, this integrated approach aids in enhancing cost-effectiveness, reducing GHG emissions by improving process efficiency, and minimizing waste generation, leading to a more sustainable and ecologically conscious biodiesel production process.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview on Biodiesel

Biodiesel, also referred to as fatty acid methyl ester (FAME), is manufactured through the transesterification process, which involves reacting vegetable oils or animal fats with methanol. The transesterification of oils or fat is as shown in Figure 2.1. Basically, biodiesel compared to petroleum-centered diesel has similarity in characteristics and composition such as viscosity, number of cetane, phase changes and energy content. Therefore, it can be directly used in any compression ignition (CI) diesel engine without requiring modifications, especially when blended with petroleum-based diesel. Biodiesel emits lower levels of GHG and possesses a higher cetane ignition rating and lubricity compared to petroleum-based diesel which make biodiesel one of the most common biofuels worldwide (Lim S & Teong L, 2010).

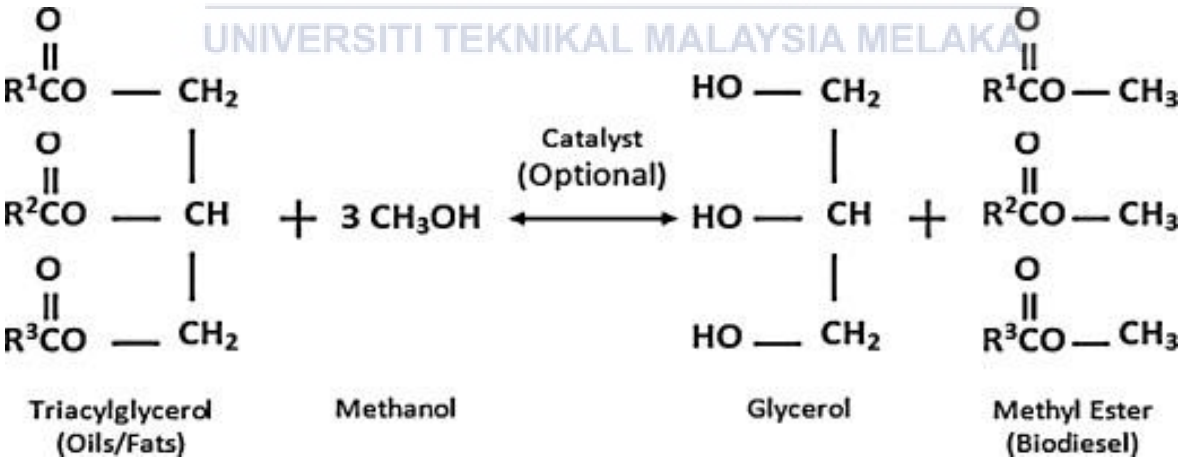


Figure 2.1 General equation for transesterification of triacylglycerol (Lim & Teong, 2010)

At the year of 1900, vegetable oils were used in the diesel engine by Rudolf Diesel, the inventor of diesel engine where the engine is named after him. In the Paris World Fair, he

demonstrated the usage of peanut oil as fuel for the engine. Usage of vegetable oils were continued to be use until year 1920 due to the uprise of petroleum-based diesel. Due to the lower cost, higher availability and subsidies given by government, petroleum-based diesel almost eliminated vegetable oils in the market. However, petroleum-based diesel has lower viscosity compared to vegetable oils.

To comply with the changes, manufacturers altered the diesel engine to utilize the lower viscosity and thus rendered the usage of vegetable oils impractical. Shortage in supply and safety problem of fossil fuels in 1970 had re-sparked the idea of developing vegetable oils as an alternative energy source to replace fossil fuels. Refinement of vegetable oils must be made to convert them into a quality fuel as the altered engine is not suitable for direct application of vegetable oils with high viscosity and low volatility. Methods such as pyrolysis, microemulsification and blending were investigated to reduce the viscosity of vegetable oils. However, these methods pose problems such as contamination and carbon deposition inside engine. As a result, the transesterification process has emerged as the most practical method for transforming vegetable oils for CI engine usage (Lim & Teong, 2010).

2.2 Biodiesel Statistics

According to Sustainability Report 2022 by Shell (one of the largest global traders and blenders of biofuels), Shell globally incorporated approximately 9.5 billion litres of biofuels into its petrol and diesel, an increase from 9.1 billion litres in 2021. Notably, this figure encompasses roughly 3 billion litres sourced from their joint venture Raízen in Brazil (Shell shareholding 44%, not Shell operated), in contrast to 3.2 billion litres in 2021. Bio-components were purchased by Shell for production, fuel blending and trading as shown in Figure 2.2. Some biofuel feedstocks are considered violation in term of human rights, biodiversity and emission of carbon into the atmosphere. All the feedstocks purchased were certified as sustainable under credible sustainability standards.

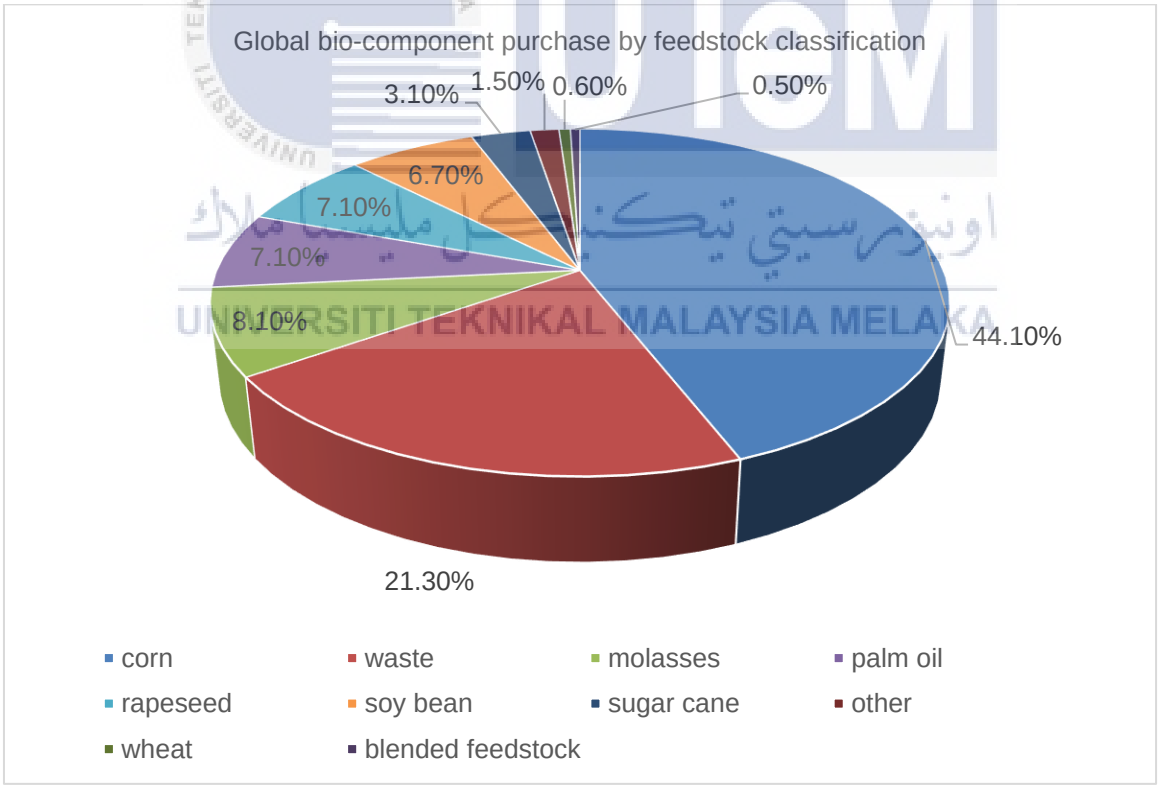


Figure 2.2 Global bio-component purchase by feedstock classification (https://reports.shell.com/sustainability-report/2022/achieving-net-zero-emissions/fuelling-mobility/biofuels.html)

2.3 Biodiesel Pros and Cons

Biodiesel offers several advantages and disadvantages as shown in Table 2.1. One significant pro is that it is an energy source that renewable, which produced from organic materials that can be replenished. This makes biodiesel an alternative to fossil fuels which are finite resources. Additionally, biodiesel combustion generates no net carbon impact since the carbon dioxide emitted during combustion is counterbalanced by the carbon dioxide absorbed during the growth of the plants utilized for biodiesel production. The fuel also produces fewer harmful emissions compared to traditional diesel, contributing to improved air quality. Biodiesel exhibits superior lubricating characteristics than traditional diesel, which enhances durability of engine by reducing wear and tear. Furthermore, biodiesel boasts cetane number higher than diesel, signifying better ignition quality and potentially leading to smoother engine operation. The environmentally friendly nature of biodiesel harmonizes with the worldwide initiative for cleaner and more sustainable energy sources.

However, biodiesel also comes with its set of challenges. One notable con is the competition for resources. As the demand for biodiesel increases, there may be competition for the same agricultural resources needed for food production, leading to potential conflicts between fuel and food production. Biodiesel production costs more compared to traditional diesel, partly due to the expense of feedstock and refining processes. Higher cloud and pour points are additional drawbacks, as biodiesel tends to gel at higher temperatures, potentially causing fuel system issues in colder climates. These challenges highlight the need for ongoing research and development to address the economic and technical limitations of biodiesel, ensuring it becomes a more viable and widespread alternative in the future.

Table 2.1 Biodiesel Pros and Cons

Pros	Cons
• Renewable Source • No Carbon Impact • Less Harmful Emission • Better lubrication • Higher cetane number • Environmentally safe • Works with most engine	• Competition of resources • Higher cost • Higher cloud point • Higher pour point

2.4 Type of Feedstock

Biofuels derived from different feedstocks are classified into four main categories such as first generation, second generation, third generation and fourth generation biodiesel. The categorization is based on the availability, properties and characteristics of the feedstock employed in their production (Ghosh & Halder, 2022).

Table 2.2 shows the examples for edible and non-edible feedstock for biodiesel. First generation biodiesels are produced from edible feedstocks, for example palm, soybean, rapeseed, peanut, olive, corn, safflower, rice bran, castor, linseed, sunflower, milkweed seed, and coconut. Second generation biodiesel is produced from non-edible feedstocks like *Jatropha curcas*, *Madhuca indica*, *Salvadora oleoides*, *Hevea brasilensis* and Jojoba. Third generation biofuels are produced from microalgae through the anaerobic digestion process. However, commercialization of these biofuels is not expected until around 2050. The concept of fourth generation biofuels revolves around using sustainable feedstocks to efficiently capture and store CO_2. Various CO_2-absorbing biomasses are utilized to produce biodiesel, similar to other types of feedstocks.

Table 2.2 Type of Feedstock

Type of feedstock	Examples
Edible	Palm, soybean, rapeseed, peanut, olive, corn, safflower, rice bran, castor, linseed, sunflower, milkweed seed, coconut
Non-edible	*Jatropha curcas*, *Madhuca indica*, *Salvadora oleoides*, *Hevea brasilensis*, Jojoba

2.4.1 Non-edible Feedstock

Biodiesel produced with non-edible feedstock is known as second generation biodiesel. Non-edible feedstocks were explored due to the expensive price and shortage of edible feedstocks. Researchers changed their focus from edible feedstocks to non-edible feedstocks under few reasons such as to preserve the environment, non-edible feedstocks lower cost, reduce food disparity and utilize the resources in rural areas. *Jatropha curcas* and *Hevea brasiliensis* are non-edible feedstocks used in biodiesel production.

2.5 Type of Catalyst

Unquestionably, catalysts have a vital role in accelerating the transformation rate of feedstock to biodiesel. By decreasing the activation energy requirement without undergoing significant changes in the process, the catalyst aids in transesterification. Both homogeneous and heterogeneous catalysts can be utilized to complete the biodiesel catalytic process. Heterogeneous catalysts operate in a separate phase from the reactant, while homogeneous catalysts function within the same phase as the reactant, making them indistinguishable. Numerous catalysts have been used throughout the years to enhance the quality of biodiesel. Figure 2.3 illustrates various categories of catalysts used to produce biodiesel.

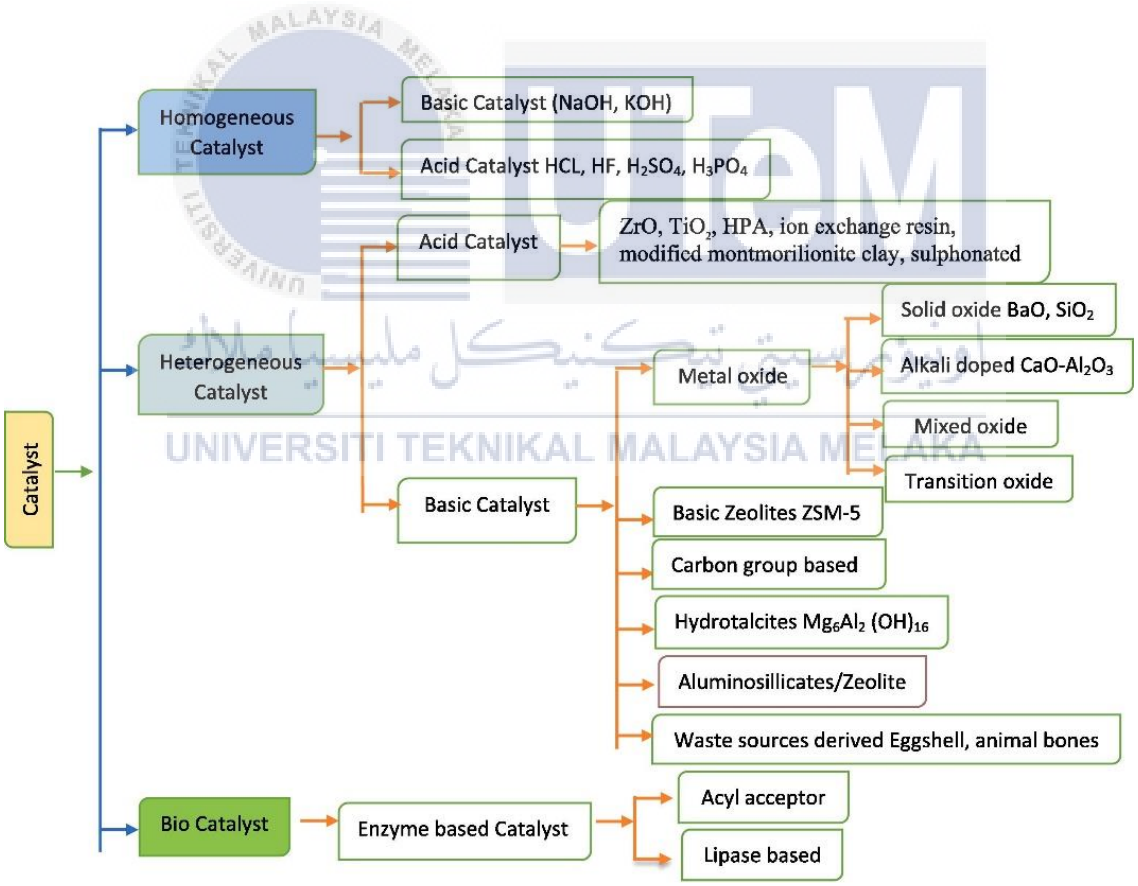


Figure 2.3 Classification of different catalyst (Ghosh & Halder, 2022)

2.5.1 Homogeneous Catalyst vs Heterogeneous Catalyst

Homogeneous catalysis is a chemistry process involving substances in the same phase such as solid, liquid or gaseous. Homogenous catalyst can be categorized into basic catalyst and acid catalyst. Homogeneous alkaline catalysts react faster comparing to acid catalyst under gentle process circumstances. If the free fatty acid (FFA) amount of the triglyceride sources more than 2%, they can lead to soap creation. Sodium hydroxide (NaOH) and potassium hydroxide (KOH) are commonly utilized in regular alkaline-biodiesel generation. On the contrary, homogeneous acid catalyst is insensible to the existence of FFAs in triglyceride sources which make them appropriate for low-degree oil. Their catalysis acceleration is quieter compared to an alkaline catalyst. Hydrochloric acid (HCl) and sulfuric acid (H_2SO_4) are great acid catalysts in biodiesel generation reaction. Homogeneous catalysts are cheaper, easier to obtain and would provide adequate performance under gentle reaction circumstances. They also have disadvantages such as segregation of catalyst from the liquid blend , reactor deterioration and saponification reaction as by-product. Catalysts that commonly used are sodium hydroxide (NaOH) and potassium hydroxide (KOH) as basic, sulfuric acid (H_2SO_4) and hydrochloric acid (HCl) as acidic.

In the other hand, heterogeneous catalysis is a chemical process involving substances in the different phase such as solid, liquid or gaseous. Heterogeneous catalyst can be categorized into basic catalyst and acid catalyst and are usually in solid state. They provide a surface for the reaction to occur. The advantages of heterogeneous catalyst are easier separation of the catalyst from biodiesel product and reduction of need for neutralization. Commonly used catalysts are lithium (Li), calcium oxide (CaO) and magnesium oxide (MgO) (Maheshwari et al., 2022). Table 2.3 lists the type of catalyst, their components, examples with advantages and disadvantages. Table 2.4 shows the comparison between homogeneous and heterogeneous

catalysts in few parameters such as rate of reaction, reusability, post treatment, methodology, presence of water or FFA and cost.

Table 2.3 Summary of homogeneous and heterogeneous catalyst classification (Jume et al., 2020)

Type of catalyst	Components	Common example	Advantages	Disadvantages
Homogeneous	Alkaline Acidic	KOH, NaOH, H_2SO_4, HCl, H_3PO_4	Ease to use, short reaction time	Sensitive to high FFA content feedstock and slow rate of reaction
Heterogeneous	Solid	Shells, bones, ashes	Reusable, easy separation, no soap formation, non-toxic, high catalytic activity	Long reaction time, high temperature, unwanted byproducts production

Table 2.4 Comparison of homogeneous and heterogeneous catalysts in transesterification process (Maheshwari et al., 2022)

Properties	Homogeneous catalysts	Heterogeneous catalyst
Rate of Reaction	Rapid	Moderate conversion
Reusability	Possible	Not possible
Post Treatment	Not recoverable	Recoverable
Methodology	Limited utilisation of continuous methods	Persistent fixed-bed operation is conceivable
Presence of H_2O/FFA	Sensitive	Not sensitive
Cost	High	Lower

2.6 Biodiesel Production Technology

Biodiesel production is competitive in terms of being a low cost, sustainable and ecologically friendly energy source. There are many methods and technologies in biodiesel production such as pyrolysis, transesterification, emulsification and direct blending as shown in Table 2.5 along with their description, advantages and disadvantages. The properties of the feedstock during oil extraction process decide the biodiesel production method (Abusweireh R, Rajamohan N & Vasseghian Y, 2022). Crude oil must undergo different process to convert from high to low viscosity biodiesel and achieve the desired quality to be able to use in diesel engines (Ghosh & Halder, 2022). However, compared to other techniques, transesterification is the most practical commercial procedure (Khan et al., 2014; S. P. Singh & Singh, 2010).

Table 2.5 Summary of biodiesel production method with advantages and disadvantages

Method	Description	Advantages	Disadvantages
Transesterification	Chemical reaction converting triglycerides to biodiesel	• Well-established and widely used method • High conversion efficiency • Can utilize a variety of feedstocks • Produces high-quality biodiesel	• Requires careful control of reaction conditions • Byproduct glycerol generation • Sensitivity to impurities in feedstock
Pyrolysis	Thermal decomposition of organic materials to bio-oil	• Can utilize a wide range of feedstocks, including biomass and waste oils • Bio-oil can be further processed into biodiesel or other biofuels	• Complex process requiring high temperatures and absence of oxygen • Yield and composition of bio-oil can vary based on feedstock
Emulsification	Formation of stable mixtures for efficient transesterification	• Enhances reaction rates and biodiesel yield • Uniform mixing of reactants • Can use different feedstocks and alcohol types	• Requires the use of surfactants and co-surfactants • Additional processing steps for surfactant removal and separation of phases
Direct Blending	Mixing biodiesel with petroleum diesel fuel	• Easy incorporation into existing diesel infrastructure • Gradual transition to biodiesel • Reduced emissions and improved lubricity	• Limited percentage of biodiesel in blends due to compatibility and regulatory requirements • Reliance on petroleum diesel fuel

2.6.1 Transesterification

The most widely used technique for creating biodiesel is transesterification because the fuel it yields has qualities that are identical to those of regular diesel (B. Karmakar, S. Lalthazuala Rokhum, G. Halder, 2022). In transesterification, triglyceride-containing vegetable feedstock or fat reacts with alcohol and an appropriate catalyst to create ester and glycerol at the process' conclusion. As illustrated in Figure 2.4, the transesterification process transforms triglycerides into diglycerides, monoglycerides and fatty acid methyl esters in three successive phases.

However, recovering extra methanol reduces the transesterification process's total cost. Due to the high solubility of glycerol at higher methanol percentages, glycerol separation becomes laborious at lower methanol percentages. Therefore, methanol concentrations above or below the ideal range impact the biodiesel output. Most often utilised alcohols are methanol and ethanol. Methanolysis occurs when methanol is used in the transesterification process. Because methanol is poorly soluble, careful blending of methanol with oil is crucial. The end product is known as FAME in the last step. Depending on the amount of FFA in the feedstock, biodiesel is either created using a single-stage transesterification with an alkali catalyst or a two-stage esterification with an acidic catalyst followed by transesterification (Ghosh & Halder, 2022). Properties of feedstock can be determined using gas chromatography-mass spectrometry (GCMS).

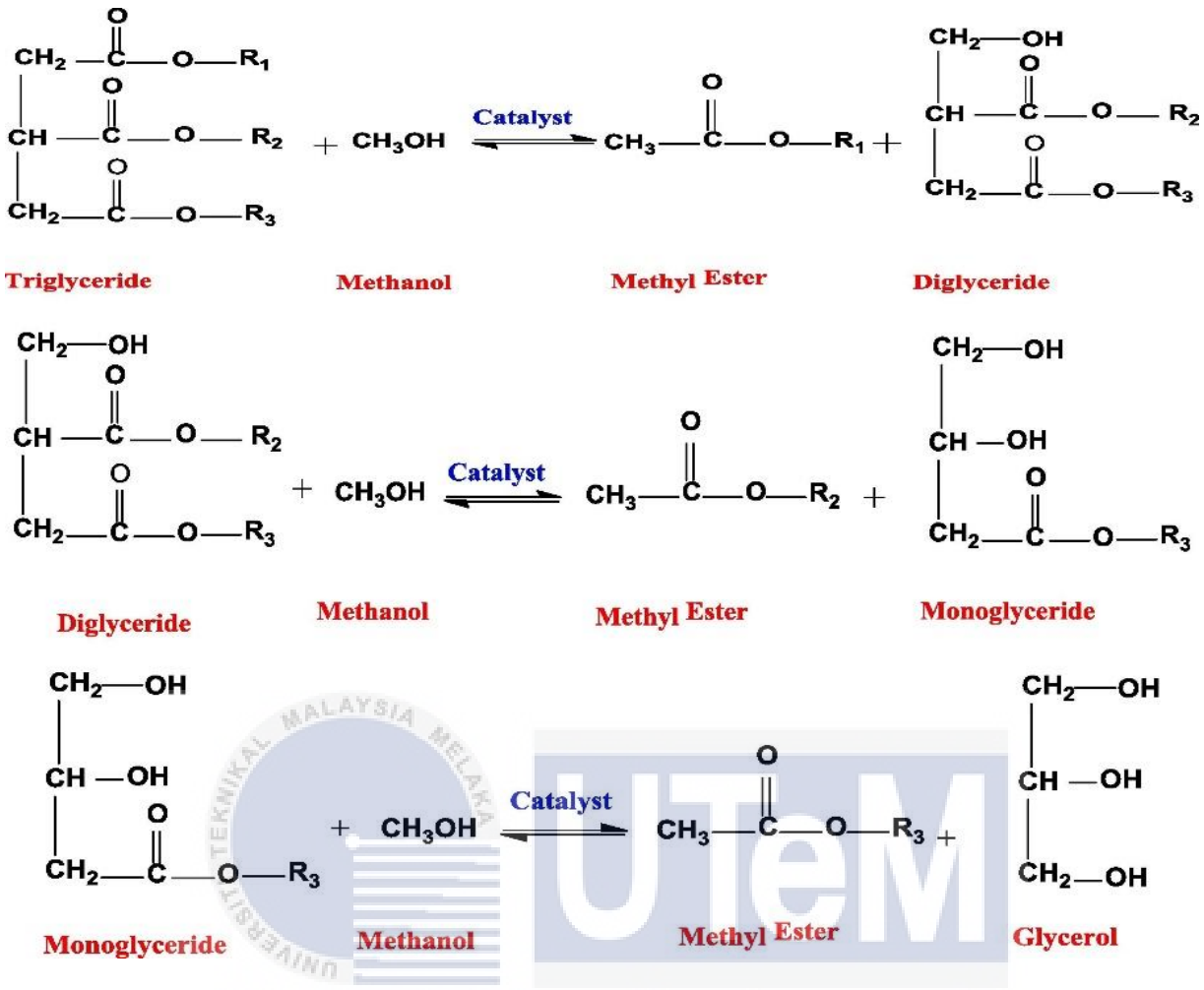


Figure 2.4 Overall reaction of transesterification (Ghosh & Halder, 2022)

2.6.2 Two-step Transesterification

Two-step transesterification consists of two processes: acid esterification followed by transesterification. Acid esterification is a process in which triglycerides are treated with an acid to reduce the level of FFA present in the feedstock. It is performed by preparing the feedstock to react with strong acid, such as sulfuric acid (H_2SO_4) or hydrochloric acid (HCl), to decrease the FFA percentage of the feedstock until it reaches less than 5% of the acid value, allowing the transesterification process to proceed with the feedstock. This is necessary because the conditions for feedstock to undergo transesterification require an FFA content of

less than 5%. High FFA levels can lead to soap formation which is undesirable in biodiesel production (Cao et al., 2022; Thoai et al., 2017).

2.7 Microwave in Biodiesel Production

In recent years, microwave energy has become increasingly significant for its capability to accelerate reaction rates (Chen et al., 2017). Microwave irradiation also known as MWI which is a form of electromagnetic radiation, have the ability to heat polar molecules in reactants. As a result, these polar molecules align themselves with the electromagnetic field of the microwaves and generate heat through friction, leading to an acceleration in reaction rates. Additionally, microwaves can also enhance reaction rates by causing the uncoupling of electron spins associated with atoms. These combined effects make microwave energy an effective tool for promoting faster reactions. Table 2.6 presents a comparison between three different heating methods for biodiesel preparation via the transesterification reaction (Gnaneswar Gude et al., 2013).

Few studies have been conducted to explore the impact of microwave heating on biodiesel production (Athar et al., 2022; Chuah et al., 2017; Hong et al., 2016). These studies have demonstrated that microwave-assisted chemical reactions outperform other synthetic techniques. Microwave heating systems have been shown to enhance reaction rates, increase product yields and improve the purity of the resulting products. Table 2.7 shows the summary of microwave-enhanced transesterification of different feedstock. Recent study focused on the production of biodiesel using a microwave heating system resulted in improved yields. These findings highlight the potential of microwave heating as a promising method for enhancing the efficiency and effectiveness of biodiesel production processes (Lin et al., 2015). Methanol, being a polar molecule with a high dielectric constant, is often preferred for microwave-assisted

transesterification reactions. Its characteristics make it suitable for efficient heat generation and promoting the desired chemical transformations in the reaction process (Nayak & Vyas, 2019).

Table 2.6 Comparison between heating mechanisms for biodiesel production (Gnaneswar Gude et al., 2013)

Characteristic/parameter	**Conventional heating**	**Supercritical heating**	**Microwave heating**
Reaction time	Long (1-2 hr)	Short (<1 hr)	Very short (0.05-0.1 hr)
Reaction temperature (°C)	40-100	250-400	40-100
Reaction pressure	Atmospheric	High pressure (35-60 MPa)	Atmospheric
Catalyst required	Yes	No	Yes/No
Heat losses	High	Moderate	Low
From of energy	Electrical energy converted to thermal energy	Electrical energy converted to thermal energy	Electrical energy applied through microwaves
Process efficiency	Low	Moderate	High
Catalyst removal	Yes	No	Yes
Soap removal	Yes	No	Yes
Advantages	Simple operation, low energy source usage	Short reaction time, easy product separation	Short reaction time, cleaner products and energy efficient
Limitations	High energy requirements, saponified products	High capital costs, pressure vessel safety	May not be efficient with feedstock containing solids

Table 2.7 Summary of microwave-enhanced transesterification of different feedstock

Feedstock	Methanol to oil molar ratio	Catalyst Type	Catalyst Loading (wt.%)	Reaction Time (min)	Reaction Temperature (°C)	Microwave Power (W)	Biodiesel Yield (%)	Researcher
Papaya oil	9.5:1	NaOH	0.95 wt.%	3.5	62.33	700	99.30	(Nayak & Vyas, 2019)
WCO	8:1	CaO	4 wt.%	75	65	300	98.2	(Hsiao et al., 2020)
WCO	7.46:1	Calcium diglyceroxide (CaDG)	1.03 wt.%	15	62	-	94.86	(Gupta & Rathod, 2018)
JCO	9:1	Fe_3O_4@SiO_2-SO_3 H	8 w.t%	210	80	-	98±1	(Changmai et al., 2021)
WCO	12:1	NaOH	0.8 wt.%	2	65	600	98.2	(Hsiao et al., 2021)
Palm oil	5:1	$Ca(OH)_2$	0.5 wt.%	10	-	-	96	(Marwan & Indarti, 2016)
JCO	18:1	CaO	4 wt.%	5	-	800	94	(Buasri & Loryuenyong, 2017)
Wet microalgae	-	Graphene Oxide (GO)	5 wt.%	40	90	500-600	95.1	(Cheng et al., 2016)

Feedstock	Methanol to oil molar ratio	Catalyst Type	Catalyst Loading (wt.%)	Reaction Time (min)	Reaction Temperature (°C)	Microwave Power (W)	Biodiesel Yield (%)	Researcher
Ceiba pentandra oil	0.6:1	KOH	0.84 wt.%	388 s	-	-	96.19	(Silitonga et al., 2020)
Camelina oil	6.91:1	KOH	1.26 wt.%	5.85	65-90	-	95.31	(Rokni et al., 2022)
Chicken feather meal oil (CFMO)	8:1	CaO	1 wt.%	5	-	500	95	(Zhang et al., 2022)
WCO	0.3:1	KOH	1 wt.%	60	60	-	97.4	(Hassan & Smith, 2020)
NO-RSO blend (6:4)	25:1	$Fe_2(SO_4)_3$	10 wt.%	120	65	150	98.77 ± 0.16 wt.%	(Falowo et al., 2019)
WCCO	7:1	KOH	0.65 wt.%	9.6	-	180-450	96.44	(Sharma et al., 2019)

2.8 Variables in Biodiesel Production

Key factors influencing biodiesel production efficiency and yield include feedstock type and composition, catalyst selection, reaction conditions (temperature, time, alcohol-to-oil molar ratio, agitation speed), fatty acid composition, water content, mass transfer, oil composition and residence time (Changmai et al., 2020) The selection of appropriate feedstocks is crucial, considering factors like large-scale utilization, costs, and oil content, as they significantly impact production costs. The chemical composition of feedstocks plays a vital role in determining biodiesel characteristics. The catalyst used in transesterification affects reaction rate and product quality, while alcohol type and ratio influence conversion efficiency and properties. Reaction temperature, time, and water presence affect kinetics and equilibrium. Adequate mixing is essential for proper reactant-catalyst contact during transesterification. Purification methods ensure biodiesel quality, and optimizing these variables enables producers to enhance efficiency, increase yields, and create high-quality biodiesel meeting specifications for a renewable and environmentally friendly alternative to conventional diesel fuel. Figure 2.5 illustrates variables affecting transesterification.

Figure 2.5 Variables in transesterification reaction

2.9 Biodiesel Properties

ASTM D6751 and EN 14214 are both standards for biodiesel fuel. ASTM 6751 was developed by the American Society for Testing and Materials (ASTM) and is the standard for biodiesel fuel in the United States. It covers the requirements and test methods for biodiesel fuel, including purity, stability and performance characteristics. It is widely used internationally except country with cold weather. EN 14214 was developed by the European Committee for Standardization (CEN) and is the standard for biodiesel fuel in the European Union. It is based on the German DIN 51606 standard and covers the requirements and test methods for biodiesel fuel, including purity, stability and performance characteristics.

EN 14214 is widely used in Europe (EU) because it ensures the quality and consistency of biodiesel fuel produced and used within the EU. While both standards are similar in many respects, they differ in some technical details, such as the allowable limits for certain impurities. The choice of standard used often depends on the region and regulations governing the use of biodiesel fuel in that area. Therefore, Europe uses EN 14214 as the standard for biodiesel fuel because it was developed by CEN and covers the requirements specific to the European Union. ASTM 975 is the standard for petrodiesel production (Yusuff A, Gbadamosi A, Atray N, 2022; Yusuff A, Popoola L, Adeniyi D, Olutoye M, 2022; Abdullahi K, Ojonugwa S, Yusuff A, Umaru M, Mohammed I, Olutoye M, Aberuagba F, 2023; Demirbas A, 2009). Table 2.8 shows the properties and qualities of biodiesel according to EN 14214 standard. Table 2.9 shows the comparison properties of different biodiesel production standards such as ASTM D975, ASTM D6751 and EN 14214 (Atabani et al., 2012).

EN is used in country with cold weather due to cold start condition. According to EU regulations, a cold start is described as the engine initiation either after achieving thermal

equilibrium with the surrounding environment or within the initial 5 minutes until the coolant temperature reaches 70 °C. When the engine operates under cold start conditions, the elevated viscosity of diesel at lower temperatures adversely affects atomization and mixing properties. Consequently, this phenomenon leads to unavoidable elevated levels of unburned hydrocarbon (UHC) and carbon monoxide (CO) emissions during combustion within the cylinder (Chaudhari et al., 2021; Xu et al., 2024).

European biodiesel standards, exemplified by EN 14214, establish stringent criteria for the cold flow properties of biodiesel, crucial for its performance in low-temperature environments. These properties, including Cloud Point, which indicates the temperature of crystal formation causing cloudiness in the fuel, Cold Filter Plugging Point (CFPP), representing the lowest temperature for unhindered fuel passage through a standardized filtration test, and Pour Point, denoting the temperature at which the fuel maintains flow under gravitational force, collectively determine the resilience of biodiesel in cold conditions. Compliance with these standards ensures that biodiesel can function effectively in cold weather, preventing issues such as clogging in fuel lines and filters, and maintaining optimal operation in diesel engines.

Table 2.8 Properties and qualities of biodiesel according to EN 14214 (Pham et al., 2022)

Property	Test method	Limits	Units
Ester content	EN 14103	96.5 min	% (mol/mol)
Density, 15°C	EN ISO 3675, EN ISO 12185	860-900	kg/m^3
Kinematic viscosity, 40°C	EN ISO 3104, ISO 3105	3.5-5.0	mm^2/s
Flash point	EN ISO 3679	120 min	°C
Sulfer content	EN ISO 20846, EN ISO 20884	10.0 max	mg/kg
Carbon residue (10% distillation residue)	EN ISO 10370	0.30 max	%(mo;/mol)
Cetane number	EN ISO 5165	51 min	-
Sulfated ash	ISO 3987	0.02 max	% (mol/mol)
Water content	EN ISO 12937	500 max	mg/kg
Total contamination	EN 12662	24 max	mg/kg
Copper strip corrosion (3h, 50°C)	EN ISO 2160	1	Degree of corrosion
Oxidation stability, 110°C	EN 14112	6.0 min	h
Acid value	EN 14104	0.5 max	mg KOH/g
Iodine value	EN 14111	120 max	g I_2/100 g
Linolenic acid content	EN14103	12.0 max	% (mol/mol)
Polyunsaturated (≥4 double bonds) methyl esters	EN 14103	1 max	% (mol/mol)
Methanol content	EN 14110	0.2 max	% (mol/mol)
MAG content	EN 14105	0.80 max	% (mol/mol)
DAG content	EN 14105	0.2 max	% (mol/mol)
TAG content	EN 14105	0.2 max	% (mol/mol)
Free glycerol	EN 14105 EN14106	0.020 max	% (mol/mol)
Total glycerol	EN 14105	0.25 max	% (mol/mol)
Group I metals (Na, K)	EN 14108 EN 14109	5.0 max	mg/kg
Group II metals (Na, K)	EN 14538	5.0 max	mg/kg
Phosphorus content	EN 14107	10.0 max	mg/kg

Table 2.9 Properties and qualities of biodiesel in comparison with conventional diesel according to ASTM D6751 (Atabani et al., 2012; Mahesha et al., 2022; Moser et al., 2023)

Fuel Properties	Diesel fuel	Biodiesel		Test method	
	ASTM D975	ASTM D6751	EN 14214	ASTM	EN
Density 15 ˚C (kg/m^3)	850	880	860-900	D1298	EN ISO 3675/12185
Viscosity at 40 ˚C (cSt)	2.6	1.9-6.0	3.5-5.0	D-445	EN ISO 3104
Cetane number	40-55	Min. 47	Min. 51	D-613	EN ISO 5165
Iodine number	38.3	-	Max. 120	-	EN 14111
Calorific value (MJ/kg)	42-46	-	35	-	EN 14214
Acid (Neutralization) value (mg KOH/g)	0.062	Max.0.50	Max.0.5	D-664	EN 14104
Pour point (˚C)	-35	-15-16	-	D 97	-
Flash point (˚C)	60-80	Min. 100-170	>120	D-93	ISO DIS 3679
Cloud point (˚C)	-20	-3-12	-	D-2500	-
Cold filter plugging point (˚C)	-25	19	Max. +5	D-6371	EN 14214
Copper strip corrosion (3h at 50 ˚C)	1	Max. 3	Min.1	D-130	EN ISO 2160
Carbon (% wt)	84-87	77	-	-	-
Hydrogen (% wt)	12-16	12	-	-	-
Oxygen (% wt)	0-0.31	11	-	-	-
Methanol content % (m/m)	-	-	Max. 0.20	-	EN 14110
Water and sediment content (%vol)	0.05	Max. 0.05	Max. 500[b]	D2709	EN ISO 12937
Ash content % (w/w,)	0.01	0.02	0.02		EN 14214
Sulphur % (m/m)	0.05	Max. 0.05	10[b]	D 5453	EN ISO 20846
Sulphated ash % (m/m)	-	Max. 0.02	Max. 0.02	D-874	EN ISO 3987
Phosphorus content	-	Max. 0.001	10[b]	D-4951	EN 14107
Free glycerine % (m/m)	-	Max. 0.02	Max.0.02	D-6584	EN 14105/14106
Total glycerine % (m/m)	-	Max. 0.24	0.25	D-6584	EN 14105
Monoglyceride % (m/m)	-	0.52	0.8	-	EN 14105
Diglyceride % (m/m)	-	-	0.2	-	EN 14105
Triglyceride % (m/m)	-	-	0.2	-	EN 14105
CCR 100% (% mass)	0.17 (0.1)[d]	Max. 0.05	Max. 0.03	D-4530	EN ISO10370
Distillation temperature (%)	-	Max. 360 ˚C	-	D-1160	-
Oxidation stability (hrs, 110 ˚C)	-	3 min	6 min	D-675	EN 14112
Lubricity (HFRR; µm)	685	314	-	-	-

2.10 Biodiesel Optimization Method

Optimization in biodiesel production is important because it can increase the yield of biodiesel given a limited amount of feedstock, resulting in more efficient use of resources and potentially lower cost. The yield of biodiesel depends on a variety of factors, including the type and quality of the feedstock, the reaction conditions, the catalyst used, and the method of separation and purification. Optimization involves systematically varying these factors to determine the combination that maximizes the yield of biodiesel. By optimizing the process, it may be possible to increase the yield of biodiesel and reduce the amount of waste and by-products generated during production. This can make biodiesel a more cost-effective and environmentally friendly alternative to petroleum-based diesel fuels.

Additionally, optimizing the production process can also lead to improvements in the quality and performance of the biodiesel, making it a more viable option for use in diesel engines. There are several optimization methods such as Taguchi Method (Aniza R, Chen W, Yang F, Pugazhendh A, Singh Y, 2022), Response Surface Methodology (RSM) (Abdullahi et al., 2023; Sai et al., 2020) and Artificial Neural Network (ANN) (Agus Haryanto et al., 2020; Aniza et al., 2022; El-Shafay et al., 2022; Farobie et al., 2015; Filho & Viegas, 2018; Jerniti et al., 2016; Mogilicharla & Reddy, 2021; Okonkwo et al., 2023; Vinoth Arul Raj et al., 2021) were applied in biodiesel production. Table 2.10 shows the summary of optimization method used to produce various type of feedstocks with heterogeneous catalyst (shell, CaO). Table 2.11 shows the summary of optimization method focusing on RSO. From the table, most of the optimization are RSM and ANN focused.

Table 2.10 Summary of optimization method used to produce various type of feedstocks with heterogeneous catalyst (shell, CaO)

Type of feedstock	Heterogeneous catalyst (shell)	Variables	Yield	Optimization method	Authors
Waste cooking oil (WCO)	Walnut shell, sawdust	MR, catalyst loading, reaction time, reaction temperature	92.25%	RSM, ANN	(Maleki et al., 2023)
Marine fishmeal plant (MFMP) oil	Crab shell	MR, catalyst loading, reaction time, reaction temperature	87.47 - 88.16	RSM	(Karkal et al., 2023)
Waste frying oil (WFO)	Chicken eggshell	MR, catalyst loading, reaction time, reaction temperature	93.27%	Taguchi method	(Ur Rahman et al., 2021)
Microalgae dry biomass	Egg shell waste	Reaction time, catalyst loading, stirring intensity	86.41%	RSM	(Pandit & Fulekar, 2017)
WCO	Crab shell, plantain peels	Reaction temperature, catalyst loading , reaction time, MR	93%	RSM	(Amenaghawon et al., 2022)
WCO	Eggshell	Catalyst calcinations temperature, catalyst calcinations time, catalyst loading, MR, reaction temperature and reaction time	96.6 ± 0.05%, 96.3 ± 0.10%	RSM, Taguchi method	(T. S. Singh & Verma, 2019)

Table 2.11 Summary of optimization method focusing on RSO

Type of feedstock	Heterogeneous catalyst (shell)	Variables	Yield	Optimization method	R^2	Authors
RSO	Fluorite (CaF_2)	MR, catalyst loading, reaction time	-	RSM, ANN	0.8179, 0.993	(Sai Bharadwaj, S, et al., 2019)
RSO	Eggshell (CaO)	MR, catalyst loading, reaction time	99.7%	RSM, ANN	0.9566, 0.9976	(Sai Bharadwaj, Singh, et al., 2019)
RSO	Fluorite (CaF_2)	MR, catalyst loading, reaction time	95.95%	RSM, ANN	0.8732, 0.9885	(A. V. S. L. Sai et al., 2019)
RSO	Eggshell (CaO)	MR, reaction time, catalyst loading	97.84 %	RSM, ANN	0.9118, 0.99	(Sai et al., 2020)
RSO	*Achatina fulica* (CaO)	Reaction temperature, reaction time, MR, and catalyst loading	96.70%	RSM	0.994	(Aisien & Aisien, 2023)

2.10.1 Taguchi Method (TM)

The TM is one of the statistical methods also known as robust design methods developed by Genichi Taguchi. Its purpose is to improve the quality of manufactured products and can be applied to various fields such as engineering, biotechnology and marketing. Taguchi experiment design is commonly used to optimize the process parameter values to improve the quality properties of a product. Conventional experiment design methods are basically complicated despite being not that accurate. Besides that, conventional methods require more runs of experiments as the number of process parameters increases.

TM utilizes a special design of orthogonal arrays (OA) that allows whole parameter space to be studied with a small number of experiments. This method has other advantages as well such as reduce the variability of the response variable in term of economy, determine the best solution for optimum process conditions in experiments, improve the production of Research and Development (R&D) process and can be applied to whatever process. The difference between the experimental value and the intended value is then determined using a loss function.

To quantify the performance characteristic deviating from the target value, Taguchi suggests using the loss function. The loss function's value is subsequently converted into the Signal-to-noise ratio (SNR), η. TM utilizes *SNR* for measurement of variance from the experiment design. *SNR* is the ratio of the mean (signal) to the standard deviation (noise). *SNR* is a logarithmic function used in optimization of the process or product design and minimization of the variability. The *SNR* also can be interpreted as the variance inverse and the maximization of *SNR* reduces the variability of the process opposed to unfavourable changes in the surrounding environment. Appropriate *SNR* function must be chosen in the *SNR* analysis. There are 3 categories of *SNR* performance characteristics which is smaller-

the-better, larger-the-better and nominal-the-better. According to the objectives of the problem, these characteristics values describe different characteristic of quality. The formulae are as shown below:

$$\text{Nominal-the-better: } \eta = S/N_T = 10\log\frac{\bar{y}}{s_y^2} \tag{2.1}$$

$$\text{Larger-the-better (maximize): } \eta = S/N_L = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{2.2}$$

$$\text{Smaller-the-better (minimize): } \eta = S/N_S = -10\,log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \tag{2.3}$$

where $\bar{y}$ is the average of observed data, s_y^2 is the variance of *y*, *n* is the number of observations and *y* is the observed data (Ginting & Tambunan, 2018; Nalbant et al., 2007).

Expression of *SNR* are in decibel scale. Every single *SNR* characteristic has their own usage. Nominal-the-better as in Equation 2.1 is used for reduction of variability surrounding a specific target. Larger-the-better as in Equation 2.2 is used for optimization of system with largest response possible. Smaller-the-better as in Equation 2.3 is used for optimization of system with smallest response possible. In biodiesel production, the purpose is to optimize the yield of biodiesel. Therefore, larger-the-better is suitable to use in this research. By comparing the equality of different means, the analysis of variance (ANOVA) is used to determine whether process parameters or factors are statistically significant. Results of ANOVA display each factor values of sum of square deviations from the mean (SS), degree of freedom (DOF), mean of squares (MS), ratio between the mean of squares effect and the mean of squares error (F-value) and probability value (P-value). Several studies have been done using TM for optimization of biodiesel production (Agrawal et al., 2020; Aniza et al., 2022).

2.10.2 Artificial Neural Network (ANN)

An ANN is a set of computational algorithms that emulates the operations of the human nervous system, aiming to replicate how the human brain analyzes and processes information. Similar to the human brain's ability to recognize patterns and categorize information, ANNs are adept at performing analogous tasks. They exhibit self-learning capabilities, offering effective solutions for addressing complex problems that may pose challenges for human resolution. Artificial neural networks have broad applications across various domains of Artificial Intelligence, notably in Deep Learning models. They find utility in financial operations, marketing research, enterprise planning, trading, business analytics, product maintenance and other areas.

Furthermore, neural networks prove highly effective in time series forecasting, enabling accurate predictions of future trends based on historical data. Their application extends to classification and regression tasks, such as image classification and sentiment analysis. Additionally, neural networks play a pivotal role in diverse data science disciplines, including natural language processing, computer vision, recommender systems and sentiment analysis. The inherent advantages of neural networks, such as parallel processing capabilities, internal data storage, self-learning abilities and robustness in handling messy data, position them as powerful tools for solving intricate problems and fostering innovation across numerous industries (Kılıç et al., 2020; Maleki et al., 2023).

ANNs are indeed based on the biological neural network found in the human brain as shown in Figure 2.6. ANNs draw inspiration from the structure and functioning of the human biological neuron as shown in Table 2.12. In an ANN, the basic building blocks correspond to elements found in a biological neuron. For example, the input layer in an ANN is akin to dendrites in a biological neuron, as it receives signals or information. The neurons

within the hidden layers simulate the processing capabilities of the biological neuron's soma. The weights assigned to connections between neurons in an ANN are analogous to the strength of synapses in a biological neuron, influencing the flow of information. Finally, the output layer in an ANN corresponds to the axon, providing the ultimate result or output. Similar to their biological counterparts, ANNs continuously learn from observational data or training sets.

In the human brain, a neuron serves as the fundamental unit of the nervous system, communicating through electrical and chemical signals. With over 86 billion neurons, each neuron is connected to numerous others, receiving inputs and transmitting signals to the cell body. In ANNs, the artificial neuron, also known as a node, functions similarly to a biological neuron. It utilizes an activation function, which determines the output based on the input. Typical neural networks architecture consist of three layer: input layer, hidden layer and output layer as shown in Figure 2.7. Input nodes receive information and present it as activation values, with each node assigned a specific number. This information then propagates through the network, passing through hidden nodes, until it reaches the output nodes.

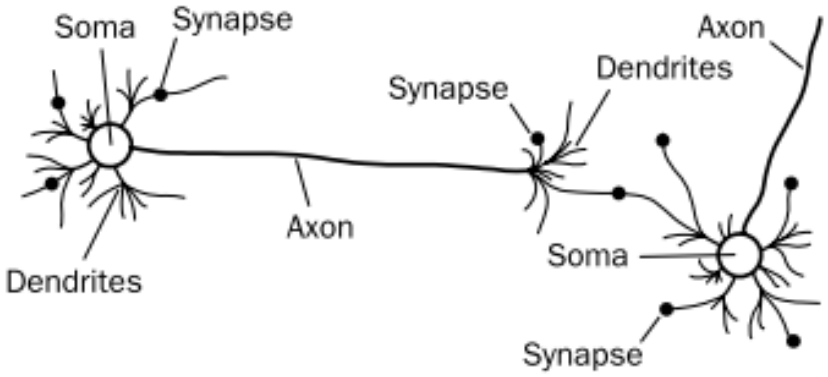


Figure 2.6 Biological neural network (Negnevitsky, 2005)

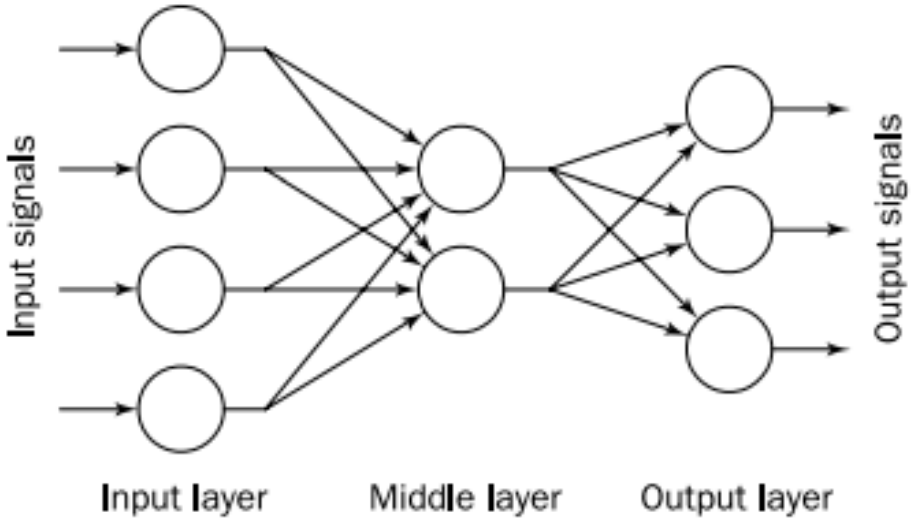


Figure 2.7 Typical architecture of ANN (Negnevitsky, 2005)

Table 2.12 Analogy and function of biological neural network and ANN

Biological neural network	ANN	Functions
Soma	Neuron	Process information
Dendrite	Input	Receives information
Axon	Output	Carries information to other neurons
Synapse	Weight	Junction between axon end and dendrites of other neuron

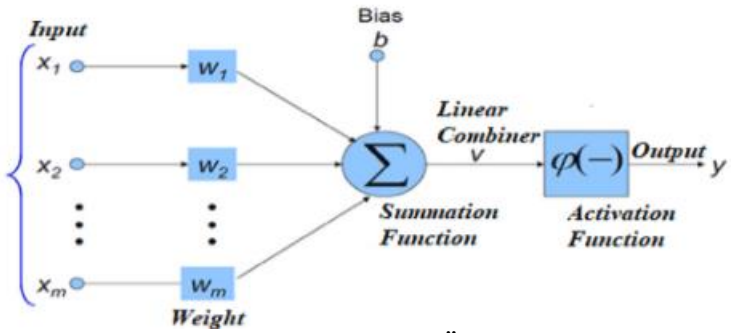


Figure 2.8 ANN model structure (Öztürk & Başar, 2022)

Figure 2.8 illustrates that a neuron can have more than one input (x_1, x_2, ..., x_m), with each input value being multiplied by a corresponding weight (w_1, w_2, ..., w_m). These weights

play a crucial role in determining the impact of inputs on the cell. In its simplest structure, the products of these multiplications are summed and sent to a transfer function, which yields the result and transforms it into an output. This fundamental principle can be extended by employing various additional functions, known as transfer functions, and adopting different network structures. The bias represents an additional constant term, usually denoted as b, which is not associated with any specific input but is added to the weighted sum before passing through the transfer function. The bias allows the neural network to account for certain offsets or shifts in the input data, providing flexibility in capturing more complex relationships (Öztürk & Başar, 2022).

Activation function (AF) also known as transfer function is a fundamental mathematic function in ANN used to connect input to output to decide whether the neurons should be activated or not. There is 3 types of AF which is log-sigmoid (LOGSIG), hyperbolic tangent-sigmoid (TANSIG) and linear (PURELIN) as shown in Figure 2.9. LOGSIG and TANSIG are used in ANN for non-linear fitting while PURELIN is used for linear fitting. LOGSIG maps input values to output values in the range of [0, 1] while TANSIG maps in the range of [-1, 1].

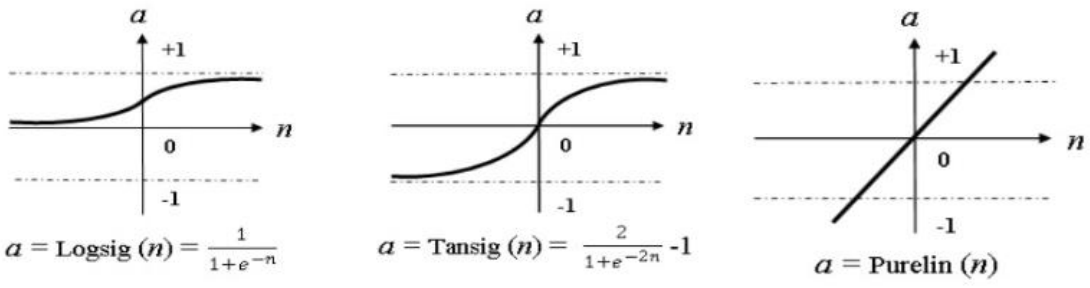


Figure 2.9 Activation function logsig, tansig and purelin (Agus Haryanto et al., 2020)

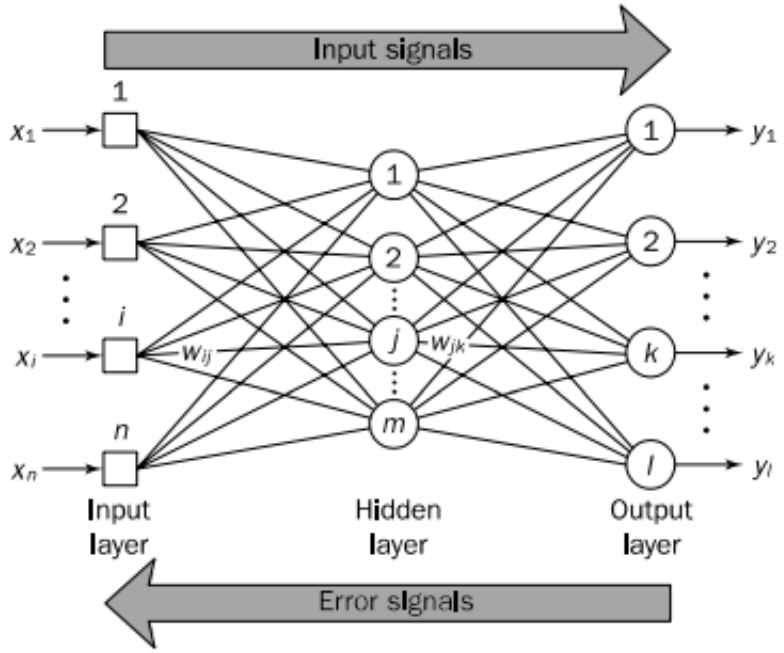


Figure 2.10 Back-propagation neural network (Negnevitsky, 2005)

The back-propagation process, depicted in Figure 2.10 involves the propagation of input signals (x_1, x_2, ..., x_n) from left to right, and error signals (e_1, e_2, ..., e_l) from right to left in the network. The symbol w_{ij} denotes the weight for the connection between neuron *i* in the input layer and neuron *j* in the hidden layer, and the symbol w_{jk} is the weight between neuron *j* in the hidden layer and neuron *k* in the output layer. The prediction error, or the difference between actual data and desired data, is computed at the output layer, and the error signals are fed back to the network to update the weights, completing one cycle. This iterative process is repeated multiple times until the predicted error is sufficiently reduced, constituting a full epoch in the training stage (Negnevitsky, 2005).

CHAPTER 3

METHODOLOGY

3.1 Introduction

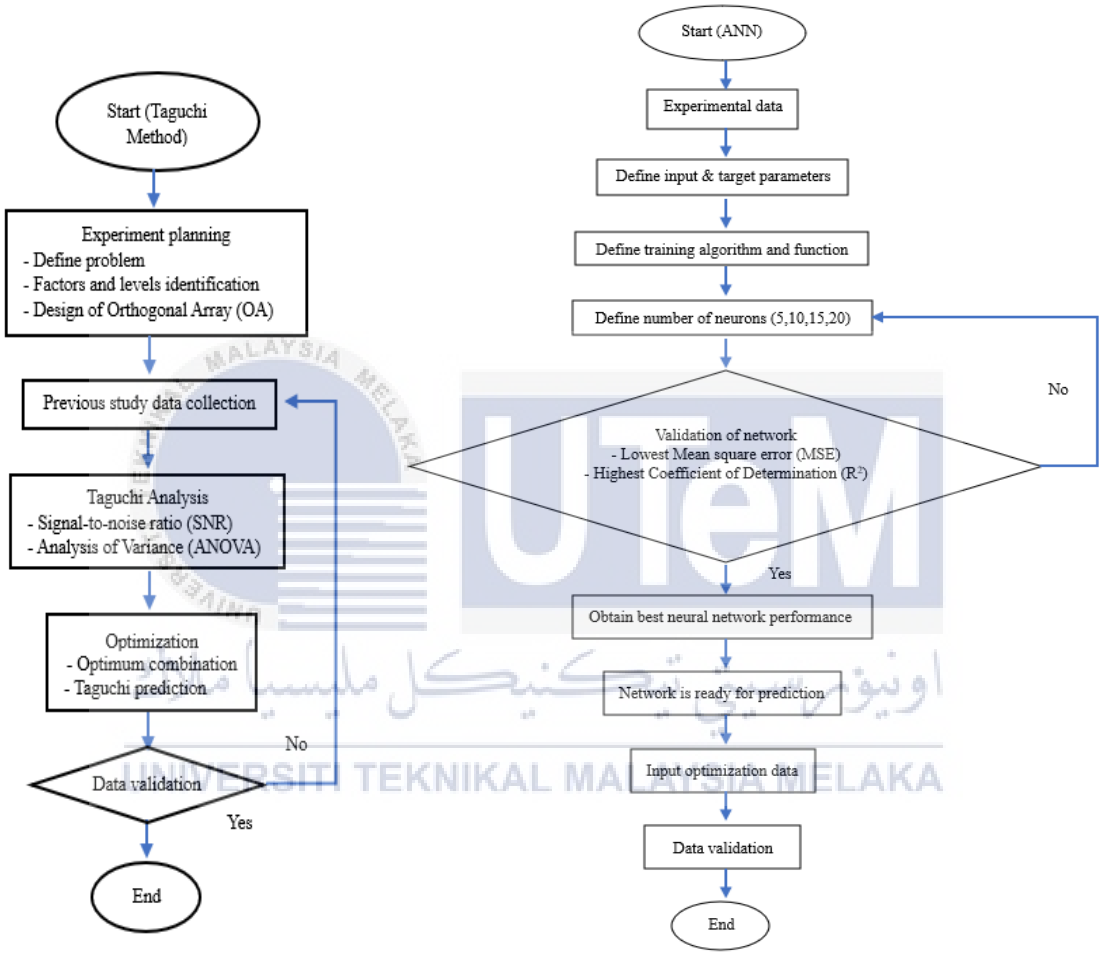
In this study, the integration of TM and ANN is applied to optimize and predict the yield of biodiesel produced from feedstocks RSO and JCO. The integration of TM and ANN has emerged as a valuable approach for optimizing complex systems and improving their performance. While not a new concept, this integration combines the statistical and experimental design principles of TM with the predictive and learning capabilities of ANN models.

TM aids in reducing problem dimensionality, identifying influential factors, and determining optimal factor levels, guiding the training and optimization process of the ANN. By leveraging the strengths of both techniques, this integration offers advantages such as enhanced prediction accuracy, reduced experimental effort, and efficient optimization of intricate systems. Consequently, the combination of TM and ANN has found applications in diverse fields, including engineering, manufacturing, quality control, and process optimization.

However, the integration of the TM and ANN in biodiesel production is relatively uncommon and lack of research (Aniza et al., 2022; Kılıç et al., 2020). In biodiesel production, the TM has been used to optimize parameters such as temperature, time and catalyst concentration, aiming for high yield and quality. ANN has been employed for modelling biodiesel properties, process optimization and predict. Although the integration of these two methods is not widely explored in the context of biodiesel production, it is an

area of potential future research for improving optimization and control strategies in the industry.

3.2 Integration of Taguchi Method and ANN Process



(a) (b)

Figure 3.1 Integration of TM and ANN flowchart (a) TM (b) ANN

Figure 3.1 illustrates the integration of TM and ANN in the experimental and optimization process. The methodology commences with the TM involving meticulous experiment planning including the problem definition, factors and levels identification. By using *OA* design, optimum experiment run can be acheived. Leveraging data from prior

studies, Taguchi analysis, encompassing *SNR* and ANOVA, is conducted to ascertain the significance of factors on the output and achieve optimal results. Subsequently, an optimization phase ensues, executing experiments with the identified optimal factor combination gleaned from the *SNR* plot and validating the model's accuracy through predictions. If the data validation is correct, then the ANN can proceed. If not, the data must be reviewed based on the experiment or previous studies.

The ANN process starts with importation and normalization of experimental data which is then separated into input and target parameters. The training alogorithm and function are determined for model training. The optimum number of neurons is selected from four sets of number (5 ,10, 15 and 20) using validation of network based on the lowest MSE and highest R^2. The ANN is trained multiple times to obtain the best neural network performance. Then, the network is ready for prediction. Optimization data from TM is inputted, and the model simulates the prediction, producing output data. Percentage error calculation is carried out to ensure the ANN model is not overfitting. Finally, the flow process concludes, and the network can be utilized for making predictions and generating insights based on the provided input parameters. This integrative methodology synergizes the strengths of TM's structured experimental design with the predictive capabilities of ANN, facilitating a thorough analysis and efficient optimization of the studied system. The PSM 1 and PSM 2 timeline are as shown in APPENDIX A and B respectively.

3.3 Minitab

Minitab is a powerful statistical software package developed by Minitab Inc., a privately owned company based in State College, Pennsylvania, United States. Founded in 1972 by Dr. Barbara F. Ryan, Thomas A. Ryan, Jr. and Paul G. Zikmund, Minitab Inc.

sought to create accessible statistical software for professionals and non-statisticians alike. Minitab has since become widely recognized and trusted in industries worldwide for data analysis and quality improvement.

The software offers a range of tools and techniques for statistical analysis, data visualization and process optimization. With its user-friendly interface, users can import, manipulate and analyze data, apply statistical methods and create insightful graphs and charts. Minitab supports quality improvement efforts through features like capability analysis, statistical process control and Six Sigma methodologies. Additionally, it enables experimental design, reliability analysis, and report generation. Minitab is a valuable tool for making data-driven decisions, improving processes and driving continuous improvement initiatives across diverse sectors.

Various studies have been conducted using TM in Minitab software. In this study, Taguchi design of experiment (DOE) and analyses such as *SNR* and ANOVA are utilized using Minitab®21.4.

3.4 Taguchi Method Optimization Application

TM is a statistical approach to optimize the performance of a system or process by identifying the key factors that affect the output and determining the optimal settings for those factors. An *OA* is a structured array used in the TM to design and conduct experiments efficiently. It is a set of predetermined experimental combinations that cover all possible factor level combinations with a minimum number of experimental runs. The key principle behind using an *OA* is to reduce the number of experiments required to obtain meaningful data while still capturing the important information about the factors being studied. By using an *OA*, the experimental design becomes more efficient, saving time and resources.

The specific choice of the *OA* depends on the number of factors and levels being investigated. The array is selected based on the desired level of interactions between factors and the desired level of precision in estimating the effects of the factors. *L27* OA was chosen due to the complexity of the study and higher precision compared to *L9* OA (Agrawal et al., 2020). The *OA* ensures that each factor is varied independently and the interactions between factors are evenly distributed across the experimental design. This allows for the identification of the main factors affecting the output and their optimal levels, while minimizing the impact of confounding factors. Table 3.1 shows the factors and levels that are going to be implement in *OA*. 5 factors used in the experiment are catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power with 3 levels (high, medium and low). Table 3.2 shows the *OA* used to design the experiments with 5 factors at three levels with a total of 27 runs. Table 3.3 shows the $L_{27}(3^5)$ *OA* with 5 factors at three levels.

Table 3.1 Factors and levels

Factors		Levels		
		1	2	3
A	Catalyst type	*CF*	*PV*	*AG*
B	Catalyst loading (wt.%)	7	9	12
C	Methanol to oil molar ratio	9	12	15
D	Reaction time (min)	5	7	9
E	Microwave power (W)	350	400	450

**CF = Corbicula Fluminea* (Asian Clam); *PV = Perna Viridis* (Green Mussel); *AG = Anadara Granosa* (Blood Clam)

Table 3.2 *OA* used to design the experiments with 5 factors at three levels, $L_{27}(3^5)$

Run No.	**Process Control Factors**				
	A	**B**	**C**	**D**	**E**
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	2	3	1
11	2	1	2	3	2
12	2	1	2	3	3
13	2	2	3	1	1
14	2	2	3	1	2
15	2	2	3	1	3
16	2	3	1	2	1
17	2	3	1	2	2
18	2	3	1	2	3
19	3	1	3	2	1
20	3	1	3	2	2
21	3	1	3	2	3
22	3	2	1	3	1
23	3	2	1	3	2
24	3	2	1	3	3
25	3	3	2	1	1
26	3	3	2	1	2
27	3	3	2	1	3

Table 3.3 $L_{27}(3^5)$ *OA* with 5 factors at three levels

Run no.	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)
1	CF	7	9	5	350
2	CF	7	9	5	400
3	CF	7	9	5	450
4	CF	9	12	7	350
5	CF	9	12	7	400
6	CF	9	12	7	450
7	CF	12	15	9	350
8	CF	12	15	9	400
9	CF	12	15	9	450
10	PV	7	12	9	350
11	PV	7	12	9	400
12	PV	7	12	9	450
13	PV	9	15	5	350
14	PV	9	15	5	400
15	PV	9	15	5	450
16	PV	12	9	7	350
17	PV	12	9	7	400
18	PV	12	9	7	450
19	AG	7	15	7	350
20	AG	7	15	7	400
21	AG	7	15	7	450
22	AG	9	9	9	350
23	AG	9	9	9	400
24	AG	9	9	9	450
25	AG	12	12	5	350
26	AG	12	12	5	400
27	AG	12	12	5	450

3.5 Analysis of Variance (ANOVA)

ANOVA, or Analysis of Variance, is a statistical method used to compare the means of two or more groups. It helps determine if there are significant differences among the means of the groups being compared. The technique involves partitioning the total variability in the data into different components to evaluate the variation between groups and within groups. By comparing the variation between groups to the variation within groups, ANOVA assesses if the observed differences in means are statistically significant.

The ANOVA process involves several steps. First, hypotheses are formulated, with the null hypothesis assuming no significant differences among the group means and the alternative hypothesis suggesting at least one group mean is significantly different. Next, variability is calculated using sum of squares (SS) for each source of variation, including total sum of square (SST), SS between groups and SS within groups. DOF are calculated for each source of variation, and mean squares are obtained by dividing the SS by the corresponding DOF. The *F*-value is then calculated as the ratio of the MS between groups to the MS within groups. By comparing the *F*-value to the critical value or calculating the *P*-value, a decision is made regarding the rejection or acceptance of the null hypothesis.

ANOVA is a widely used statistical technique in various fields. It provides a reliable method to compare means and determine if differences among groups are statistically significant. By utilizing ANOVA, researchers can gain insights into the effects of different factors or treatments on the mean outcome, making it valuable for experimental studies and hypothesis testing. ANOVA's versatility allows for the examination of multiple groups or treatments simultaneously, making it a powerful tool for analyzing data with complex designs.

3.6 MATLAB

MATLAB, short for "MATrix LABoratory," is a powerful numerical computing and programming software developed by MathWorks which is co-founded by Jack Little and Cleve Moler. MATLAB provides a comprehensive environment for algorithm development, data analysis, visualization and numerical computations. With its extensive library of functions and toolboxes, MATLAB enables engineers, scientists and researchers to work with matrices, vectors and arrays, perform mathematical operations, optimize algorithms, process signals and images, design control systems and implement machine learning techniques. Its user-friendly programming language and interactive environment facilitate rapid prototyping and exploration of algorithms.

MATLAB's exceptional plotting and visualization capabilities allow for the creation of 2D and 3D plots, histograms, surface plots, animations and interactive graphics. It also has a vibrant user community and a File Exchange platform for sharing codes and toolboxes. Widely used in academia, research institutions and industries such as engineering, finance and data analytics. MATLAB is a versatile tool for solving complex mathematical problems, analyzing data and facilitating research and development across various fields. MATLAB software was widely employed by numerous studies for outcome prediction (Agus Haryanto et al., 2020; Farobie et al., 2015; Kumar et al., 2023; Okonkwo et al., 2023; Vinoth Arul Raj et al., 2021). In this study, the Neural Network (nntool) command in MATLAB R2021a is utilized for modelling and training of ANN.

3.7 Levenberg-Marquardt (LM) Algorithm

Levenberg-Marquardt is type of backpropagation algorithm which operates on the error-back propagation principle. It was utilized in numerous studies for the training of ANN because it consistently achieved the highest R^2 value and demonstrated the lowest standard deviation and MSE, outperforming other algorithms (A. V. S. L. Sai et al., 2019; Agus Haryanto et al., 2020; Farobie et al., 2015; Kılıç et al., 2020; Mogilicharla & Reddy, 2021; Okonkwo et al., 2023; Sai Bharadwaj, Singh, et al., 2019; Vinoth Arul Raj et al., 2021).

The Levenberg-Marquardt (LM) algorithm is commonly used as an optimization technique for training ANNs. It combines the steepest descent method with the Gauss-Newton method to iteratively minimize the error between the predicted output and the desired output. By adjusting a damping parameter, the algorithm finds a balance between the two methods, allowing it to converge quickly even in complex, non-linear error surfaces. The algorithm calculates the gradient of the error with respect to the weights and biases of the network using backpropagation and updates them in a way that progressively reduces the error. This algorithm is widely utilized in training various types of ANNs and its effectiveness makes it a popular choice in the field.

3.8 Tangent-Sigmoid Function

The TANSIG function is employed to convert input values, spanning from negative to positive infinity, into a more manageable range of -1 to 1. Neurons incorporating this function are commonly utilized in back-propagation networks. The TANSIG function finds application in various research endeavors aimed at training ANN (A. V. S. L. Sai et al., 2019; Agrawal et al., 2020; Sai Bharadwaj et al., 2023; Sai Bharadwaj, Singh, et al., 2019).

3.9 Coefficient of Determination (R^2)

The coefficient of determination, also known as *R*-values or R^2 is a statistical measure used to assess the goodness of fit of a regression model. R^2 represents the proportion of the variance in the dependent variable that can be explained by the independent variable(s) in the model. It is a value ranging from 0 to 1, where 0 indicates that the model does not explain any of the variability in the dependent variable, and 1 indicates that the model perfectly explains all the observed variance. In essence, R^2 measures the extent to which the independent variable(s) account for the variability in the dependent variable. It serves as an indicator of the strength of the relationship between the independent and dependent variables.

However, it is important to note that R^2 does not determine causality or the validity of the model itself. Therefore, it is essential to consider other statistical measures and contextual factors when interpreting the R^2 value and assessing the effectiveness of a regression model. R^2 can be expressed in Equation 3.1:

$$R^2 = 1 - \sum_{i=0}^{n}(z_i - \hat{z}_i) / (z_i - z_m) \quad (3.1)$$

where *n* is the total number of observations or runs, $\hat{z}_i$ is the experimental value and z_i is the estimated value.

3.10 Mean Square Error (MSE)

A MSE is a statistical metric used to evaluate the accuracy and goodness of fit of a regression model. It measures the average squared difference between the predicted values

generated by the model and the actual values of the dependent variable. The MSE provides a way to quantify how well the model's predictions align with the observed data. To calculate the MSE, the differences between the predicted and actual values are squared to ensure positive values and emphasize larger errors. These squared differences are then averaged over the entire dataset, resulting in a single value that represents the average magnitude of the prediction errors.

A lower MSE indicates a better fit, with smaller prediction errors and closer alignment between the model's predictions and the actual data. The MSE is a widely used measure because it considers all the data points in the evaluation and penalizes larger errors more than smaller ones due to the squaring operation. However, it is sensitive to outliers as they can significantly influence the squared differences. Researchers and practitioners often employ MSE as a loss function to train and optimize regression models, aiming to minimize it and improve the model's prediction accuracy. MSE are used to measure the performance of ANN in multiple studies (A. V. S. L. Sai et al., 2019; Farobie et al., 2015; Filho & Viegas, 2018; Okonkwo et al., 2023; Sai Bharadwaj et al., 2023; Vinoth Arul Raj et al., 2021). MSE value is defined in Equation 3.2:

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(\hat{z}_i - z_i)^2 \tag{3.2}$$

where n is the total number of observations or data points in the dataset, $\hat{z}_i$ is the experimental value and z_i is the estimated value.

3.11 ANN Training Setting

By using nntool command in MATLAB 2021a, modelling setting of the ANN model is as shown in Figure 3.2. Feed-forward backpropagation network is used. Input data and target data needed to be converted to numeric array to import into MATLAB. TRAINLM which is LM algorithm and transfer function TANSIG is used. The performance is in terms of MSE. The number of layers (2) consists of one hidden layer and one output layer. The number of neurons can be adjustable according to the performance.

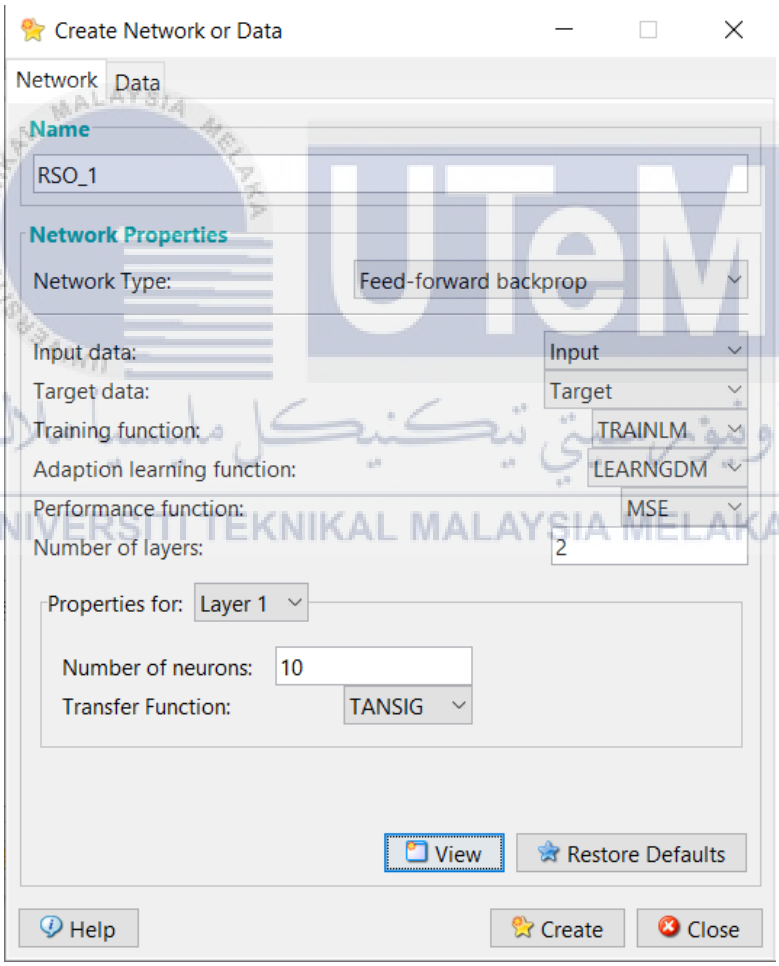


Figure 3.2ANN modelling setting

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The Taguchi experimental design is utilized to examine the influence of different process parameters on both the quality and yield of biodiesel. Key parameters of interest include catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power. Predicting the optimal combination of these parameters through regular experimentation can be challenging and time-consuming. The Taguchi optimization technique offers a systematic approach to minimize the number of experiments required while still obtaining significant results. This method allows for efficient and effective exploration of process parameters to optimize the quality and yield of biodiesel.

The *SNR* is utilized in prediction of the optimum combination of process factors, The Taguchi optimization technique evaluates the response of different process parameters and determines the optimal response based on the highest *SNR* value. This helps identify the settings that yield the most favourable outcomes in terms of quality and yield of biodiesel. The *SNR* is calculated based on three conditions as described by specific equations. While *SNR* helps in predicting the optimal response, it does not provide information about the not only determines the optimal response but also provides valuable insights into the contribution and influence of each input parameter on the output. This information helps in understanding the relative importance of different factors and their impact on the quality and yield of biodiesel production. To address this, the ANOVA test is used. The *F*-value (Fisher Test) obtained from ANOVA analysis indicates the significance of individual parameters in

affecting the output response, while the *P*-value indicates the probability of obtaining the observed *F*-value or a more extreme value if the null hypothesis is true. In the context of statistical analysis, it is used to determine the statistical significance of the observed data and assess whether the results are likely due to chance or if there is a genuine effect or relationship present. (Aniza et al., 2022; Kılıç et al., 2020).

ANN has arisen as a powerful tool for solving complex engineering problems and have gained significant popularity in recent years, particularly for predicting and optimizing nonlinear processes. ANN functions as a predictive model inspired by the biological neural system, employing interconnected neurons with adjustable synaptic weights.

The accuracy of predictions achieved by ANN surpasses that of many other statistical techniques, making it highly reliable for various applications. Consequently, in this study, the effectiveness of the optimum combination obtained from the Taguchi optimization technique is further validated using ANN. By comparing the experimental results with the predicted results, one can assess the accuracy and validity of the predictive model or equation, the closeness of the match confirms the efficacy of the identified optimum combination. This validation process strengthens the confidence in the reliability and accuracy of the chosen combination of process parameters (A. V. S. L. Sai et al., 2019; Kılıç et al., 2020).

4.2 Characteristics of Oils

Properties of JCO and RSO including acid number, kinematic viscosity at 40℃, density at 15℃, water content, iodine value and colour were tested using standard method as shown in Table 4.1. JCO has an acid number of 36.5 mg KOH/g, 34.94 mm^2/s, 0.9133 kg/L, 0.3 wt.%, 106.3 g Iodine/100g and golden yellow in colour while RSO has an acid number of 104.74 mg KOH/g, 36.96 mm^2/s, 0.9848 kg/L, 0.49 wt.%, 139 g Iodine/100g and dark brown in colour.

Table 4.1 Properties of crude JCO and RSO

Test	Unit	Method	JCO	RSO
Acid Number	mg KOH/g	ASTM D664	36.50	104.74
Kinematic Viscosity @ 40°C	mm^2/s	ASTM D445	34.94	36.96
Density @ 15°C	kg/L	ASTM D4052	0.9133	0.9848
Water Content	wt.%	EN ISO 12937	0.30	0.49
Iodine Value	g Iodine/100g	AOCS Cd 1d-92	106.3	139
Colour	-	-	Golden yellow	Dark brown

4.3 Taguchi Orthogonal Array $L_{27}(3^5)$

Based on the *OA* design $L_{27}(3^5)$, total of 27 experiments with 5 factors at 3 levels were done in previous study for both RSO and JCO biodiesel. The experimental results which is the biodiesel yield were recorded in Table 4.2 (RSO) and Table 4.3 (JCO). For RSO, highest yield was obtained at the 16th run of the experiments which is 96.2% with 12 wt.% of *PV* catalyst, 1:9 methanol to oil molar ratio, reaction time of 7 mins and microwave power of 350 W. For JCO, Highest yield was obtained at the 8th run of the experiments

which is 95.26% with 12 wt.% of *AG* catalyst, 1:15 methanol to oil molar ratio, reaction time of 9 mins and microwave power of 400 W.

Table 4.2 *OA* $L_{27}(3^5)$ experimental matrix for RSO

Run no.	Catalyst type	Catalyst loading (wt%)	Molar ratio methanol to oil	Reaction time (min)	Microwave power (W)	Yield (%)
1	*CF*	7	9	5	350	87.30
2	*CF*	7	9	5	400	88.60
3	*CF*	7	9	5	450	87.80
4	*CF*	9	12	7	350	94.20
5	*CF*	9	12	7	400	95.20
6	*CF*	9	12	7	450	94.80
7	*CF*	12	15	9	350	93.60
8	*CF*	12	15	9	400	95.60
9	*CF*	12	15	9	450	94.40
10	*PV*	7	12	9	350	90.20
11	*PV*	7	12	9	400	90.80
12	*PV*	7	12	9	450	89.60
13	*PV*	9	15	5	350	91.80
14	*PV*	9	15	5	400	92.60
15	*PV*	9	15	5	450	92.30
16	*PV*	12	9	7	350	96.20
17	*PV*	12	9	7	400	95.80
18	*PV*	12	9	7	450	96.10
19	*AG*	7	15	7	350	91.50
20	*AG*	7	15	7	400	92.20
21	*AG*	7	15	7	450	91.60
22	*AG*	9	9	9	350	90.50
23	*AG*	9	9	9	400	92.30
24	*AG*	9	9	9	450	91.10
25	*AG*	12	12	5	350	93.50
26	*AG*	12	12	5	400	95.20
27	*AG*	12	12	5	450	94.10

*Highlighted: Optimum yield

Table 4.3 *OA* $L_{27}(3^5)$ experimental matrix for JCO

Run no.	Catalyst type	Catalyst loading (wt%)	Molar ratio methanol to oil	Reaction time (min)	Microwave power (W)	Yield (%)
1	*CF*	7	9	5	350	86.40
2	*CF*	7	9	5	400	86.30
3	*CF*	7	9	5	450	87.20
4	*CF*	9	12	7	350	92.38
5	*CF*	9	12	7	400	93.80
6	*CF*	9	12	7	450	92.69
7	*CF*	12	15	9	350	92.70
8	*CF*	12	15	9	400	95.26
9	*CF*	12	15	9	450	95.15
10	*PV*	7	12	9	350	87.40
11	*PV*	7	12	9	400	90.40
12	*PV*	7	12	9	450	89.60
13	*PV*	9	15	5	350	91.30
14	*PV*	9	15	5	400	90.80
15	*PV*	9	15	5	450	90.50
16	*PV*	12	9	7	350	94.68
17	*PV*	12	9	7	400	93.50
18	*PV*	12	9	7	450	94.82
19	*AG*	7	15	7	350	91.20
20	*AG*	7	15	7	400	92.50
21	*AG*	7	15	7	450	91.70
22	*AG*	9	9	9	350	92.34
23	*AG*	9	9	9	400	93.26
24	*AG*	9	9	9	450	91.65
25	*AG*	12	12	5	350	93.50
26	*AG*	12	12	5	400	92.67
27	*AG*	12	12	5	450	93.60

*Highlighted: Optimum yield

4.3.1 Signal-to-noise Ratio (SNR)

By using the appropriate *SNR* formula based on the response type, the Taguchi method aims to find the optimal levels of input factors that maximize the *SNR* and minimize the impact of noise factors, leading to improved product or process quality. To obtain the highest yield, the larger-the-better type of *SNR* was utilized for both RSO and JCO. Table 4.4 and 4.5 present the *OA* $L_{27}(3^5)$ along with the *SNR* for RSO and JCO, respectively. A higher yield often means a stronger signal output. A stronger signal is generally easier to distinguish from background noise, leading to a higher *SNR*. For RSO, the highest *SNR* is 39.66 while for JCO, the highest *SNR* is 39.58 as highlighted.

Table 4.4 *SNR* of *OA* $L_{27}(3^5)$ for RSO

Run no.	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)	Yield (%)	SNR
1	*CF*	7	9	5	350	87.3	38.82
2	*CF*	7	9	5	400	88.6	38.95
3	*CF*	7	9	5	450	87.8	38.87
4	*CF*	9	12	7	350	94.2	39.48
5	*CF*	9	12	7	400	95.2	39.57
6	*CF*	9	12	7	450	94.8	39.54
7	*CF*	12	15	9	350	93.6	39.43
8	*CF*	12	15	9	400	95.6	39.61
9	*CF*	12	15	9	450	94.4	39.50
10	*PV*	7	12	9	350	90.2	39.10
11	*PV*	7	12	9	400	90.8	39.16
12	*PV*	7	12	9	450	89.6	39.05
13	*PV*	9	15	5	350	91.8	39.26
14	*PV*	9	15	5	400	92.6	39.33
15	*PV*	9	15	5	450	92.3	39.30
16	*PV*	12	9	7	350	96.2	39.66
17	*PV*	12	9	7	400	95.8	39.63
18	*PV*	12	9	7	450	96.1	39.65
19	*AG*	7	15	7	350	91.5	39.23
20	*AG*	7	15	7	400	92.2	39.29
21	*AG*	7	15	7	450	91.6	39.24
22	*AG*	9	9	9	350	90.5	39.13
23	*AG*	9	9	9	400	92.3	39.30
24	*AG*	9	9	9	450	91.1	39.19
25	*AG*	12	12	5	350	93.5	39.42
26	*AG*	12	12	5	400	95.2	39.57
27	*AG*	12	12	5	450	94.1	39.47

*Highlighted: Optimum yield & *SNR*

Table 4.5 *SNR* of *OA* $L_{27}(3^5)$ for JCO

Run no.	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)	Yield (%)	SNR
1	*CF*	7	9	5	350	86.40	38.73
2	*CF*	7	9	5	400	86.30	38.72
3	*CF*	7	9	5	450	87.20	38.81
4	*CF*	9	12	7	350	92.38	39.31
5	*CF*	9	12	7	400	93.80	39.44
6	*CF*	9	12	7	450	92.69	39.34
7	*CF*	12	15	9	350	92.70	39.34
8	*CF*	12	15	9	400	95.26	39.58
9	*CF*	12	15	9	450	95.15	39.57
10	*PV*	7	12	9	350	87.40	38.83
11	*PV*	7	12	9	400	90.40	39.12
12	*PV*	7	12	9	450	89.60	39.05
13	*PV*	9	15	5	350	91.30	39.21
14	*PV*	9	15	5	400	90.80	39.16
15	*PV*	9	15	5	450	90.50	39.13
16	*PV*	12	9	7	350	94.68	39.53
17	*PV*	12	9	7	400	93.50	39.42
18	*PV*	12	9	7	450	94.82	39.54
19	*AG*	7	15	7	350	91.20	39.20
20	*AG*	7	15	7	400	92.50	39.32
21	*AG*	7	15	7	450	91.70	39.25
22	*AG*	9	9	9	350	92.34	39.31
23	*AG*	9	9	9	400	93.26	39.39
24	*AG*	9	9	9	450	91.65	39.24
25	*AG*	12	12	5	350	93.50	39.42
26	*AG*	12	12	5	400	92.67	39.34
27	*AG*	12	12	5	450	93.60	39.43

*Highlighted: Optimum yield & *SNR*

Table 4.6 Response table for RSO *SNR*

Level	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)
1	39.31	39.08	39.25	39.22	39.28
2	39.35	39.35	39.37	39.48	39.38
3	39.32	39.55	39.35	39.27	39.31
Delta	0.04	0.47	0.13	0.26	0.10
Rank	5	1	3	2	4

*Highlighted: Optimum *SNR*

Table 4.7 Response table for JCO *SNR*

Level	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)
1	39.21	39.00	39.19	39.11	39.21
2	39.22	39.28	39.25	39.37	39.28
3	39.32	39.46	39.31	39.27	39.26
Delta	0.12	0.46	0.12	0.27	0.07
Rank	4	1	3	2	5

*Highlighted: Optimum *SNR*

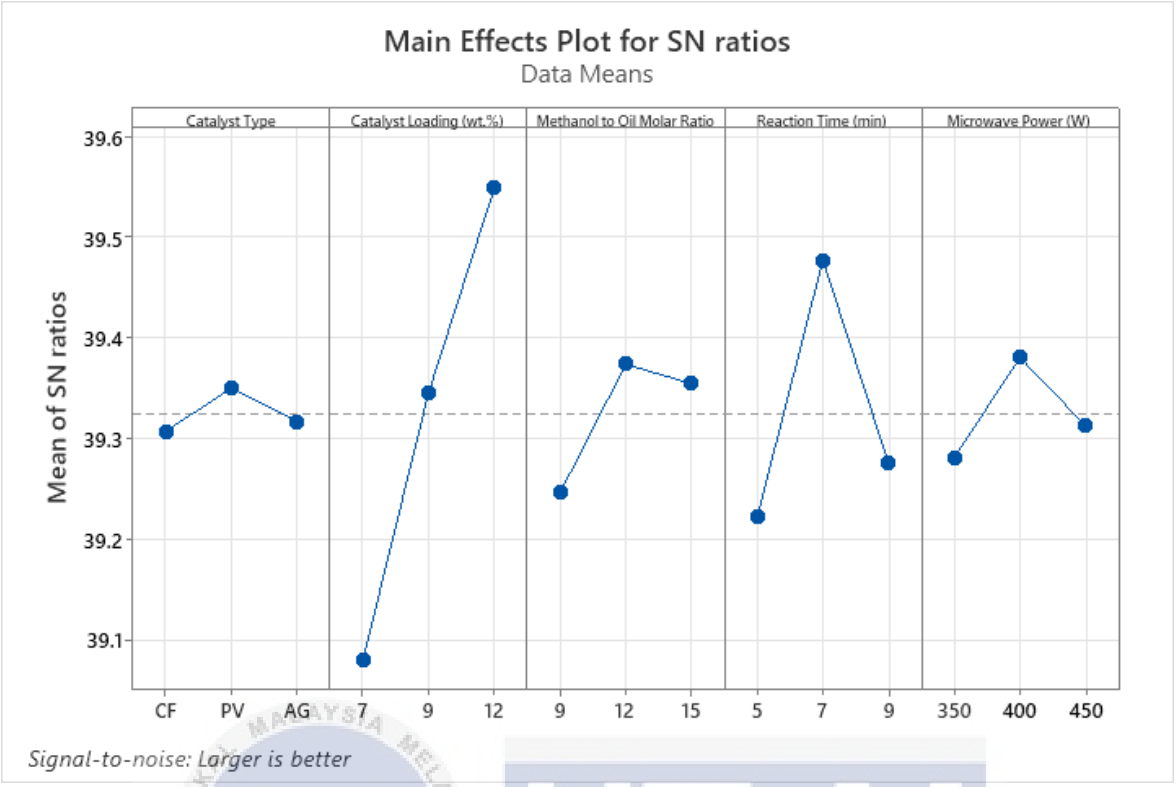


Figure 4.1 *SNR* main effects plot of RSO

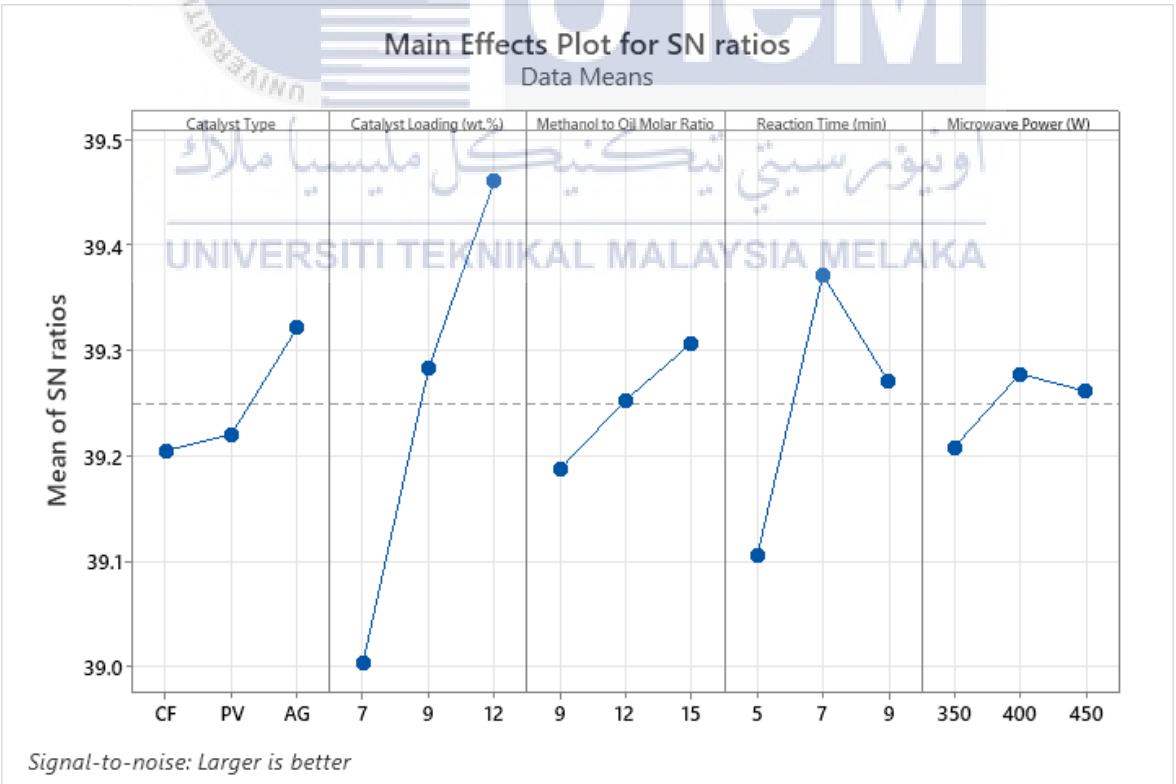


Figure 4.2 *SNR* main effects plot of JCO

27 experiments for each biodiesel were conducted based on the design matrix of L_{27} orthogonal array in previous study and the output response yield of the biodiesel is presented in Table 4.2 (RSO) and Table 4.3 (JCO). In order to predict the optimum combination of variable process parameters such as type of catalyst, catalyst concentration, methanol to oil molar ratio, reaction time and microwave power from the set of 27 experiments, *SNR* was used. The *SNR* measures the impact of noise factors on the process parameters and these noise factors cannot be controlled during the experimental process. Therefore, these factors cause variations in response data and need to be considered while analyzing the results. In general, the prediction of *SNR* is based on three mathematical equations (1-3): nominal-the-better, larger-the-better is better, smaller-the-better. In this endeavor, the objective is to increase the yield of biodiesel. Therefore, larger-the-better was chosen for *SNR*.

The order of influence of the parameters on RSO yield was B (catalyst loading) > D (reaction time) > C (methanol to oil molar ratio) > E (microwave power) > A (catalyst type) as shown in Table 4.6. For JCO yield, the order of influence of the parameters was B (catalyst loading) > D (reaction time) > C (methanol to oil molar ratio) > A (catalyst type) > E (microwave power) as shown in Table 4.7. The numerical value of the maximum point in each graph indicates the optimum range of the experimental conditions. Based on the *SNR* plots as shown in Figure 4.1, the optimum parameters for RSO were A (catalyst type) at level 2 (PV), B (catalyst loading) at level 3 (12 wt.%), C (methanol to oil molar ratio) at level 2 (1:12), D (reaction time) at level 2 (7 mins) and E (microwave power) at level 2 (400 W). For JCO, the optimum parameters for RSO were A (catalyst type) at level 3 (AG), B (catalyst loading) at level 3 (12 wt.%), C (methanol to oil molar ratio) at level 2 (1:15), D (reaction time) at level 2 (7 mins) and E (microwave power) at level 2 (400 W) as shown in Figure 4.2.

4.3.2 Analysis of Variance (ANOVA)

The Taguchi *OA* is employed to create an experimental design that efficiently investigates multiple factors with a reduced number of experiments. The mean square is calculated by summing the square of the SST and the sum of error sum of squares (SSE), which follows the ANOVA analysis. The resulting mean square is then used to generate an *F*-value. By referencing the *F*-distribution table, the corresponding *P*-value can be obtained. From the *P*-value, significance of each factor can be obtained.

ANOVA is used to model the relationship between 5 factors and one response. From the *P* value, significance of each factor can be obtained as shown in Table 4.4. *P*-value that greater than 0.05 is considered not significant. From here, factor *A* has a *P*-value of 0.083 (>0.05) is considered not significant while factor *B, C, D* and *E* with *P*-value of 0 (<0.05) are considered significant in the ANOVA. Besides that, the R^2 value obtained is 0.984 which is quite closer to 1. When R^2 is closer to 1, it signifies a strong relationship between the independent and dependent variables in a regression model. This implies that a larger proportion of the variance in the dependent variable can be explained by the independent variable(s). In practical terms, a higher R^2 suggests that the model's predictions are more accurate and closer to the actual values of the dependent variable. It indicates that the model has a better fit to the observed data, as it captures a significant amount of the variability in the dependent variable.

Table 4.8 ANOVA for RSO

Source	DOF	SS	MS	*F-value*	*P*-value	Remarks
Catalyst Type	2	0.00920	0.004600	3.09	0.074	Not Significant
Catalyst Loading (wt.%)	2	0.99927	0.499634	335.12	0.000	Significant
Methanol to Oil Molar Ratio	2	0.08554	0.042770	28.69	0.000	Significant
Reaction Time (min)	2	0.32811	0.164056	110.04	0.000	Significant
Microwave Power (W)	2	0.04647	0.023233	15.58	0.000	Significant
Error	16	0.02385	0.001491			
Total	26	1.49244				
R^2	0.984					
Adj R^2	0.974					

Table 4.9 ANOVA for JCO

Source	DOF	SS	MS	*F-value*	*P*-value	Remarks
Catalyst Type	2	0.07232	0.036162	5.34	0.017	Significant
Catalyst Loading (wt.%)	2	0.95711	0.478556	70.68	0.000	Significant
Methanol to Oil Molar Ratio	2	0.06473	0.032363	4.78	0.024	Significant
Reaction Time (min)	2	0.32617	0.163084	24.09	0.000	Significant
Microwave Power (W)	2	0.02390	0.011948	1.76	0.203	Not Significant
Error	16	0.10833	0.006771			
Total	26	1.55255				
R^2	0.930					
Adj R^2	0.887					

4.4 ANN Modelling & Training

The ANN model was developed using MATLAB R2021a. The model was structured with three parts: the input layer, hidden layer and output layer and its architecture (5-10-1) is as shown in Figure 4.3. In the input layer, five neurons were allocated, each representing a specific variable: type of catalyst, catalyst loading (wt.%), methanol to oil molar ratio, reaction time (min) and microwave power (W). Single hidden layer is utilized in this research. Some researches suggested to use only 10 neurons. To determine the suitable layer size, several trials and errors were conducted, typically ranging from 2 to 20 neurons depends on the inputs. 4 sets of neurons number (5, 10, 15 and 20) are investigated for their performances as shown in Table 4.10. From the investigation, the optimum neurons number for RSO and JCO are 10. Conversely, only one output neuron was used to represent the biodiesel yield (%).

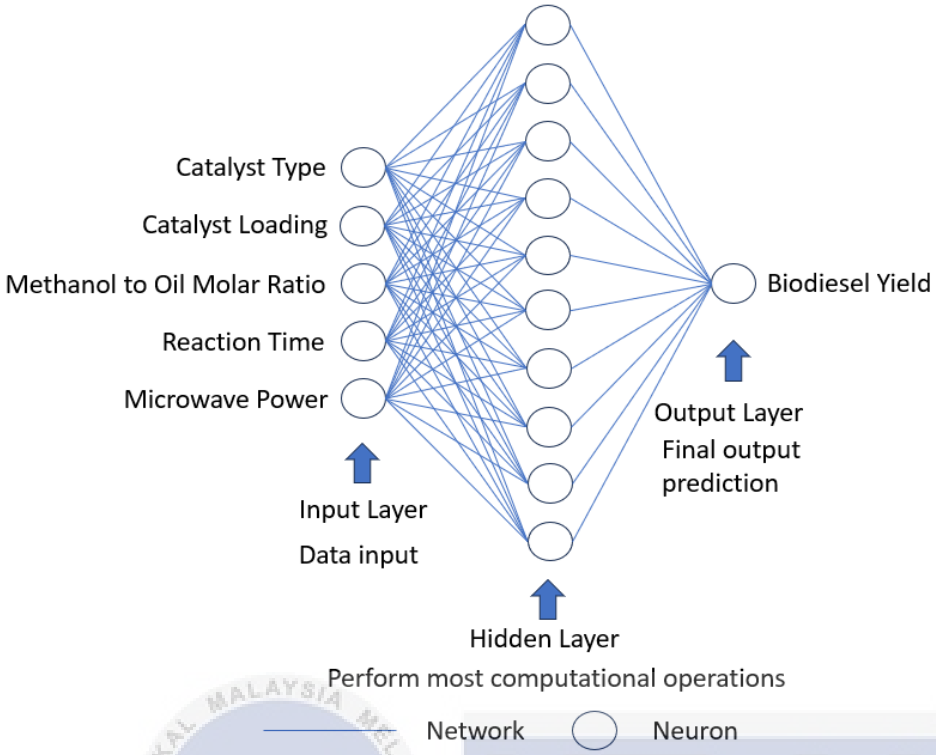


Figure 4.3ANN architechture 5-10-1

Table 4.10 Summary of performance for different number of neurons

No. of neurons	R^2				MSE
	Training	Validation	Test	All	
RSO					
5	0.98312	0.99984	0.98753	0.98454	0.0036139
10	0.99948	1	0.999	0.99953	5.64E-08
15	0.57286	0.64485	0.96539	0.58989	7.6334
20	0.96407	0.99999	0.99999	0.97288	3.57E-05
JCO					
5	0.99738	0.98476	0.99364	0.9883	0.72827
10	0.99679	0.99983	0.99998	0.99736	1.09E-03
15	0.99503	0.99714	0.99519	0.9951	0.017904
20	0.94417	0.99959	0.99994	0.97069	1.94E-02

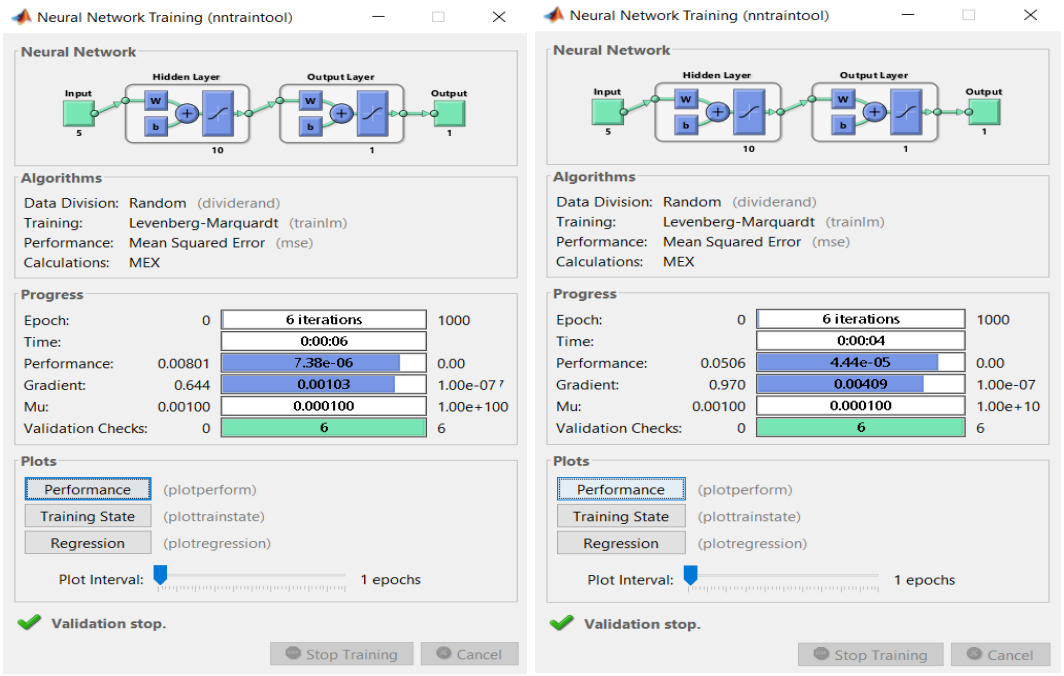
*Highlighted: Best result

Both RSO and JCO dataset consisting of 27 combinations from Taguchi *OA* as shown in Table 4.2 (RSO) and 4.3 (JCO) were utilized in the training of ANN models. The training interface is as shown in Figure 4.4. The dataset was divided into three subsets by

default: 19 data (70%) for training, 4 data (15%) for validation and 4 data (15%) for testing purposes for each model. The selection of data for each subset was done randomly. The LM algorithm was employed during the training process to minimize the MSE. Besides that, TANSIG activation function is utilized for non-linear problem and minimization of MSE. The ANN model was trained multiple times to achieve highest R^2 and lowest MSE. Concurrently, the R^2 value was targeted to be near or exactly one which indicating a strong relationship between the predicted and actual yield values. These criteria ensured the accuracy and reliability of the trained ANN model.

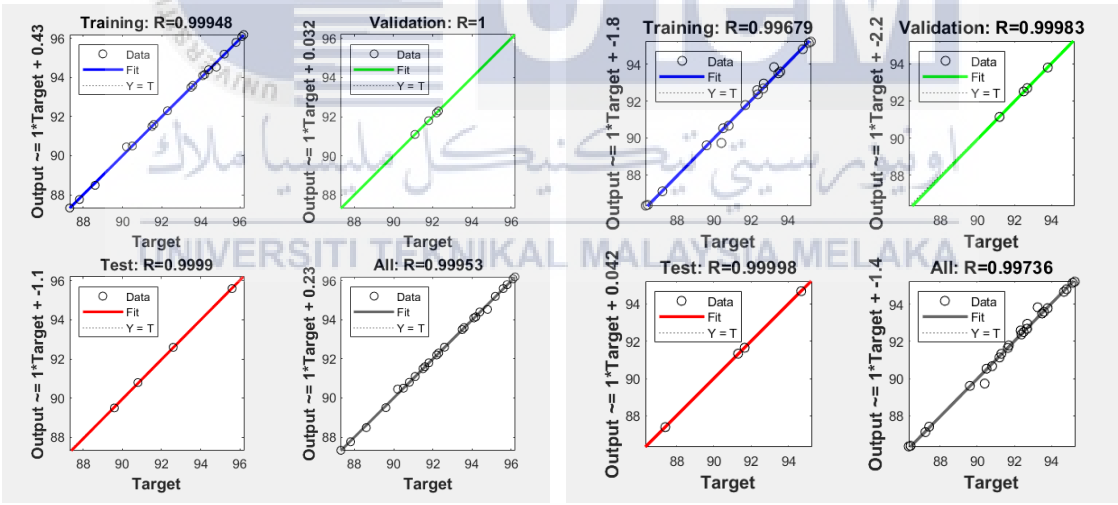
Training was halted upon reaching predefined criteria, such as achieving a performance value of 0 or completing six validation checks. This termination criterion ensures that the neural network has adequately generalized to the dataset. Training was considered complete when the lowest MSE value was achieved and the R^2 value approached or reached 1. Figure 4.5 demonstrates the R^2 values for RSO and JCO respectively, providing insights into the training progress. For RSO, R^2 of training, validation and test is 0.99948, 1, 0.999 with an overall R^2 of 0.99953. For JCO, R^2 of training, validation and test is 0.99679, 0.99983, 0.9998 with an overall R^2 of 0.99736. R^2 value between 0.7 to 1.0 is considered acceptable (Kılıç et al., 2020). This showed that the predicted and actual values have a strong correlation.

Figure 4.6 demonstrates the MSE performance of the network. For RSO, the best validation performance is 5.6442e-08 at epoch 0. For JCO, the best validation performance is 0.0010897 at epoch 0. Trials and errors must be done to obtain the best R^2 and lowest MSE. Once the best architecture is obtained, the ANN model is ready for prediction, enabling the estimation of yield based on new input data.



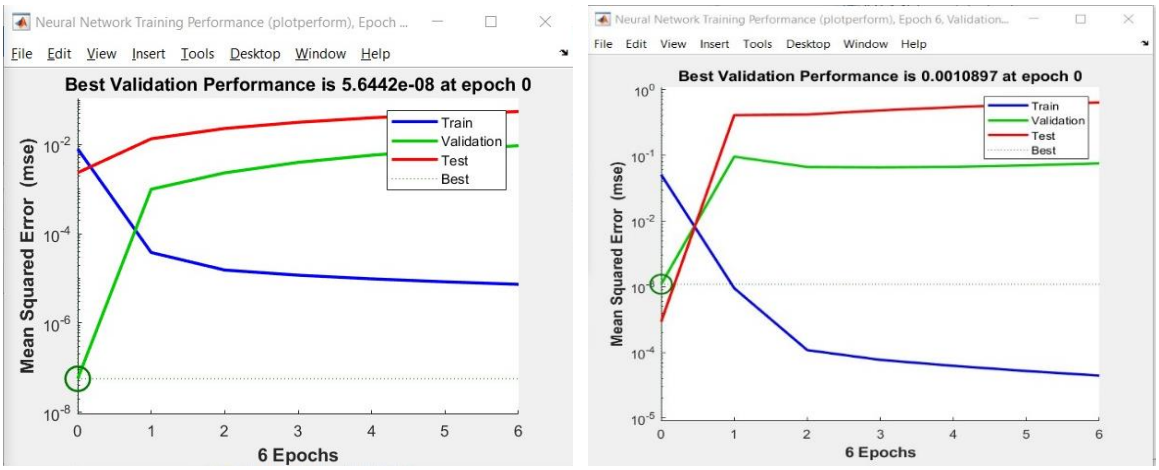
(a) (b)

Figure 4.4 ANN training interface (a) RSO (b) JCO



(a) (b)

Figure 4.5 Regression analysis (a) RSO (b) JCO



(a) (b)

Figure 4.6 MSE performance (a) RSO (b) JCO

4.5 ANN Prediction

Predictions done were recorded in Table 4.11 (RSO) and Table 4.12 (JCO). Lastly, the percentage error of actual result and predicted result were calculated. Comparison of experimental and ANN prediction were plotted as shown in Figure 4.7. The highest yield of actual result is 16th run for RSO and 8th run for JCO. The chosen ANN models predicted the highest yield for RSO and JCO correctly. Next, the optimization combinations of RSO and JCO from TM were inputed and the predictions are as shown in Table 4.13.

Table 4.11 ANN Prediction for RSO

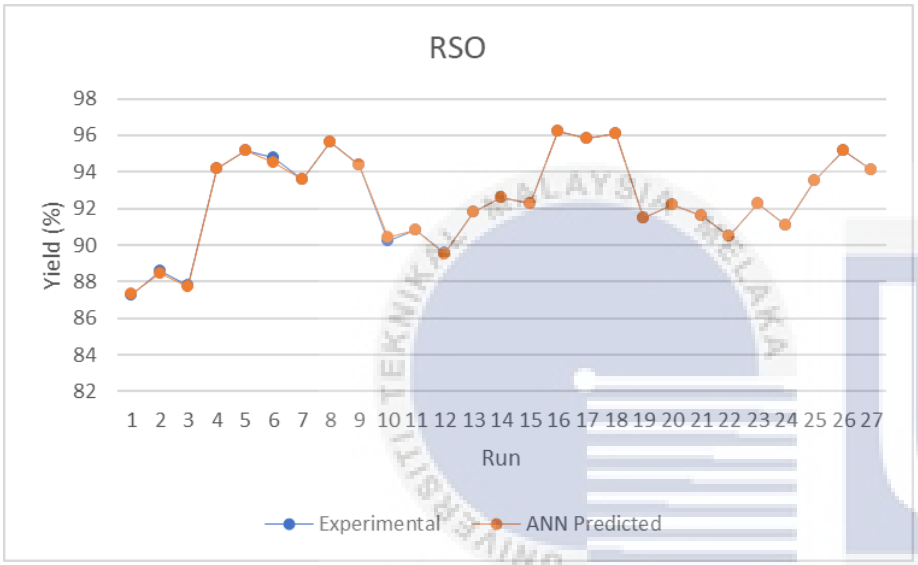
Catalyst Type	Catalyst Loading (wt.%)	Methanol to oil molar ratio	Reaction Time (min)	Microwave Power (W)	Yield (%)	ANN Predicted	% Error
CF	7	9	5	350	87.30	87.32	0.02
CF	7	9	5	400	88.60	88.48	0.14
CF	7	9	5	450	87.80	87.76	0.05
CF	9	12	7	350	94.20	94.16	0.04
CF	9	12	7	400	95.20	95.20	0.00
CF	9	12	7	450	94.80	94.53	0.28
CF	12	15	9	350	93.60	93.60	0.00
CF	12	15	9	400	95.60	95.60	0.00
CF	12	15	9	450	94.40	94.40	0.00
PV	7	12	9	350	90.20	90.45	0.28
PV	7	12	9	400	90.80	90.80	0.00
PV	7	12	9	450	89.60	89.50	0.11
PV	9	15	5	350	91.80	91.80	0.00
PV	9	15	5	400	92.60	92.60	0.00
PV	9	15	5	450	92.30	92.30	0.00
PV	12	9	7	350	96.20	96.20	0.00
PV	12	9	7	400	95.80	95.80	0.00
PV	12	9	7	450	96.10	96.10	0.00
AG	7	15	7	350	91.50	91.50	0.00
AG	7	15	7	400	92.20	92.20	0.00
AG	7	15	7	450	91.60	91.60	0.00
AG	9	9	9	350	90.50	90.50	0.00
AG	9	9	9	400	92.30	92.30	0.00
AG	9	9	9	450	91.10	91.10	0.00
AG	12	12	5	350	93.50	93.50	0.00
AG	12	12	5	400	95.20	95.20	0.00
AG	12	12	5	450	94.10	94.09	0.01

*Highlighted: Optimum yield

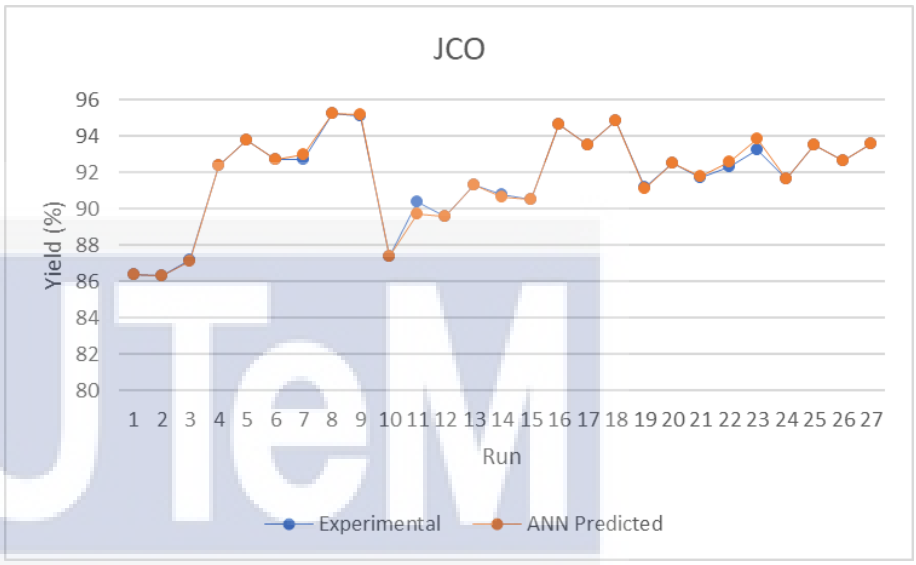
Table 4.12 ANN Prediction for JCO

Catalyst Type	Catalyst Loading	Methanol to oil molar ratio	Reaction Time (min)	Microwave Power (W)	Yield (%)	ANN Predicted	% Error
CF	7	9	5	350	86.40	86.37	0.03
CF	7	9	5	400	86.30	86.33	0.03
CF	7	9	5	450	87.20	87.10	0.11
CF	9	12	7	350	92.38	92.37	0.01
CF	9	12	7	400	93.80	93.80	0.00
CF	9	12	7	450	92.69	92.69	0.00
CF	12	15	9	350	92.70	92.95	0.27
CF	12	15	9	400	95.26	95.22	0.04
CF	12	15	9	450	95.15	95.16	0.01
PV	7	12	9	350	87.40	87.40	0.00
PV	7	12	9	400	90.40	89.73	0.74
PV	7	12	9	450	89.60	89.60	0.00
PV	9	15	5	350	91.30	91.33	0.03
PV	9	15	5	400	90.80	90.66	0.15
PV	9	15	5	450	90.50	90.53	0.03
PV	12	9	7	350	94.68	94.68	0.00
PV	12	9	7	400	93.50	93.51	0.01
PV	12	9	7	450	94.82	94.82	0.00
AG	7	15	7	350	91.20	91.13	0.08
AG	7	15	7	400	92.50	92.51	0.01
AG	7	15	7	450	91.70	91.79	0.10
AG	9	9	9	350	92.34	92.59	0.27
AG	9	9	9	400	93.26	93.84	0.62
AG	9	9	9	450	91.65	91.65	0.00
AG	12	12	5	350	93.50	93.51	0.01
AG	12	12	5	400	92.67	92.68	0.01
AG	12	12	5	450	93.60	93.60	0.00

*Highlighted: Optimum yield



(a)



(b)

Figure 4.7 Graph of experimental and ANN predicted yield for 27 runs (a) RSO (b) JCO

Table 4.13 TM & ANN prediction of optimization data

Biodiesel	Catalyst type	Catalyst loading (wt.%)	Methanol to oil molar ratio	Reaction time (min)	Microwave power (W)	Experimental Yield	Taguchi Prediction	Error (%)	ANN Prediction	Error (%)
RSO	PV	12	12	7	400	96.61	97.95	1.39	96.10	0.53
JCO	AG	12	15	7	400	95.88	96.90	1.06	95.24	0.67

Table 4.13 presents the optimum combinations for RSO and JCO based on the TM, including their experimental yields, as well as the predicted yields and percentage errors obtained through both TM and ANN. For RSO, the optimal conditions involve a 12 wt.% *PV* catalyst, a 1:12 methanol to oil molar ratio, a reaction time of 7 minutes, and 400 W microwave power. The experimental yield achieved for RSO is 96.61%, while TM and ANN predicted yields of 97.95% and 96.10%, respectively. The percentage error for TM is 1.39%, and for ANN, it is 0.53%. Similarly, the optimal combination for JCO includes a 12 wt.% *AG* catalyst, a 1:15 methanol to oil molar ratio, a reaction time of 7 minutes, and 400 W microwave power. The experimental yield for JCO is 95.88%, with TM and ANN predicting yields of 96.90% and 95.24%, respectively. The percentage error for TM is 1.06%, and for ANN, it is 0.67%.

In conclusion, the outcomes of this study reveal that both the TM and ANN demonstrate a high level of accuracy in predicting yields, with percentage errors of 1.39% and 0.53% for TM and 1.06% and 0.67% for ANN in the case of RSO and JCO, respectively. These results affirm the efficacy of both optimization approaches in reliably forecasting yields within a narrow margin of error, highlighting their suitability for predicting outcomes in the given experimental condition.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study, titled "Integrating Taguchi Method and Artificial Neural Network for Predicting and Maximizing of RSO and JCO Biodiesel Yield," aimed to investigate the combined application of the TM and ANN in optimizing biodiesel production processes. Focusing on the synthesis of RSO and JCO biodiesel, the study assessed the predictive capabilities of TM and ANN to achieve optimal yields.

The experimental results, meticulously documented in Table 4.13, underscore the successful integration of TM and ANN in predicting optimal conditions for RSO and JCO biodiesel production. The identified optimal parameters, encompassing catalyst type, catalyst loading, methanol to oil molar ratio, reaction time and microwave power, highlight the potential of this integrated approach to significantly enhance yield outcomes.

The yields obtained through experimentation closely aligned with predictions from both TM and ANN, exhibiting percentage errors well within acceptable margins. Specifically, for RSO, the experimental yield was 96.61%, while TM and ANN predicted yields of 97.95% and 96.10%, respectively. Similarly, for JCO, the experimental yield was 95.88%, with TM and ANN predicting yields of 96.90% and 95.24%, respectively.

This convergence between experimental and predicted outcomes substantiates the efficacy and reliability of the integrated TM and ANN methodology in optimizing biodiesel production processes. The identified optimal conditions, specifically tailored for RSO and JCO, serve as a robust foundation for further research and potential application in industrial-scale biodiesel production.

5.2 Recommendations

Firstly, it is advisable to conduct further optimization studies encompassing a broader spectrum of input parameters and conditions. This expanded exploration would enhance the depth of our understanding of optimal process conditions, potentially leading to even higher yields and a more robust model.

Secondly, a sensitivity analysis on the input parameters should be undertaken to gauge the model's robustness. Understanding the model's sensitivity to variations in input parameters will contribute to the reliability of predictions, ensuring that the integrated TM and ANN model can adapt to real-world variations.

Moreover, continuous experimental validation is paramount to confirming the reliability of the model under diverse conditions. Additional experiments should be conducted to validate the predictive capabilities of the integrated approach across different feedstocks and reaction conditions, thereby fortifying its practical applicability.

Furthermore, an economic feasibility analysis should be integrated into future research endeavors. This analysis would evaluate the cost-effectiveness of implementing the optimized conditions for large-scale biodiesel production, considering factors such as raw material costs, energy consumption and catalyst expenses.

Finally, the integration of contemporary machine learning methodologies enhances the robustness of our approach. Leveraging cloud services, encompassing modeling, training, and deployment, streamlines the implementation of our model. Moreover, employing APIs or endpoints for deployment facilitates convenient access to the predictive model. This modernized approach not only ensures efficiency but also aligns with current trends in machine learning, fostering a more dynamic and responsive framework.

5.3 Project Potential

The successful integration of the TM and ANN in predicting and maximizing RSO and JCO biodiesel yields unveils substantial potential for impactful projects within the biodiesel production domain. This integrated methodology stands poised to enhance overall biodiesel production efficiency. By accurately predicting optimal conditions for the synthesis of RSO and JCO biodiesel, the project addresses a crucial aspect of the production process, potentially leading to increased yields. The streamlined processes not only reduce resource consumption but also minimize waste, contributing to a more sustainable and efficient biodiesel production landscape.

Furthermore, the project has the potential to optimize costs associated with industrial-scale biodiesel production. The identified optimal parameters, serving as valuable insights, offer the prospect of cost reduction by minimizing the need for extensive experimentation and refining production processes. This economic feasibility can enhance the attractiveness of large-scale biodiesel production, aligning with industry goals of sustainability and economic viability.

A notable strength of the project lies in its adaptability to different feedstocks beyond RSO and JCO. This versatility opens avenues for tailoring the optimization approach to various raw materials, broadening the application of the technology across diverse biodiesel production scenarios. As such, the project paves the way for customizable and efficient biodiesel production strategies that can be tailored to specific feedstock characteristics.

Beyond its immediate applications, the project contributes to broader sustainability and environmental impact objectives. Improving biodiesel yield efficiency aligns with global efforts to transition towards renewable energy sources, thereby reducing greenhouse gas

emissions and mitigating the environmental footprint associated with conventional fossil fuels.

The integration of the project's findings and optimized conditions with existing industry practices represents a seamless progression towards industry standards. This potential for integration can catalyze advancements in biodiesel production methodologies, making a positive and lasting impact on the industry's operational norms and practices.

Moreover, the success of this project opens the door to further research opportunities. Future investigations could explore additional parameters, alternative feedstocks and refinements to the methodology, thereby ensuring continuous advancements in biodiesel production optimization. This ongoing pursuit of knowledge can further solidify the project's standing as a catalyst for innovation within the biodiesel industry.

In conclusion, the integration of TM and ANN for RSO and JCO biodiesel production holds considerable potential to revolutionize biodiesel production. From increased efficiency and cost savings to broader sustainability impacts, the project signifies numerous opportunities for transformative projects that align with the evolving landscape of sustainable energy production.

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APPENDICES

APPENDIX A PSM 1 Gantt Chart

WEEK / TASK	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14
PSM Topic Confirmation														
Identify problem statement, objectives and scope														
Literature review writing														
Methodology writing														
Software determination														
Data collection														
PSM 1 report drafting														
PSM 1 report draft submission														
PSM 1 report correction														
PSM 1 report submission														
PSM 1 presentation														

APPENDIX B PSM 2 Gantt Chart

WEEK / TASK	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14
TM trials														
TM validation														
ANN trials														
ANN validation														
Result and discussion writing														
Conclusion and recommendation writing														
PSM 2 report drafting														
PSM 2 report draft submission														
PSM 2 report correction														
PSM 2 report submission														
PSM 2 presentation														