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PREDICTION OF CETANE NUMBER OF VARIOUS BIODIESEL USING MATHEMATICAL MODELS

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NEAR EAST UNIVERSITY

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DEPARTMENT OF MECHANICAL ENGINEERING

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M.Sc. THESIS

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November, 2021

Approval

We certify that we have read the thesis submitted by Ahmed Muayad Rashid AL-ANI titled **"Prediction of Cetane Number of Various Biodiesels Using Mathematical Models**" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Educational Sciences.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Ahmed Muayad Rashid AL-ANI

22/11/2021

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Ahmed Muayad Rashid AL-ANI

Abstract

Prediction of Cetane Number of Various Biodiesels Using Mathematical Models

AL-ANI, Ahmed

MA, Department of Mechanical Engineering

November, 2021, 63 pages

The cetane number (CN) of the biodiesel is a very essential, which lets to reduce the quality of the biodiesel, thus affect the engine performance. In this study, a comparative study between an empirical equation (linear, linear + squared, linear + interaction and full quadratic), multilayer perceptron neural network (FMLP) and Radial Basis Neural Network (RBNN for modelling CN of biodiesel. 36 models with various combinations of parameters including (the sum of the saturated ($\sum SFAMs$), monounsaturated ($\sum MUFAMs$) and polyunsaturated ($\sum PUFAMs$)) were proposed to identify most influencing input parameters for predicting the CN. The coefficient of determination and root mean squared error were used to select the best predictive model. It is found that ME#16 and RBFNN#5 with the combination of [$\sum PUFAMs$, $\sum SFAMs$] and [$\sum MUFAMs$, $\sum PUFAMs$] respectively, are the best models for estimating the CN. Moreover, the lowest value of RMSE is recorded for the model of RBFNN#5 with the combination of [$\sum MUFAMs$, $\sum PUFAMs$] followed by ME#22 with the combination of [$\sum MUFAMs$, $\sum PUFAMs$, $\sum SFAMs$].

***Key Words**:* Biodiesel, Cetane number, machine learning, empirical equation, fatty acid profile

Abstract

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List of Abbreviations

CN: Cetane Number

$\sum SFAMs$**:** Sum of the saturated

$\sum MUFAMs$**:** Sum of the monounsaturated

$\sum PUFAMs$**:** Sum of the polyunsaturated

CHAPTER I
Introduction

This chapter includes the problems, aims, importance, limitations and related descriptions of the research.

Background

Sustainable development is the main and nominal goal of the whole world. Energy is the main engine and the active element for all growth and development. In addition, it is the basic element for all sectors of the economy and a companion to human life. Sustainable development is based primarily on protecting the environment, ensuring optimal use and equitable distribution of resources between the current generation and subsequent generations, such traditional energy does not allow the achievement of development sustainable. Thus, finding an alternative energy source like biofuel is the best solution for saving the environment.

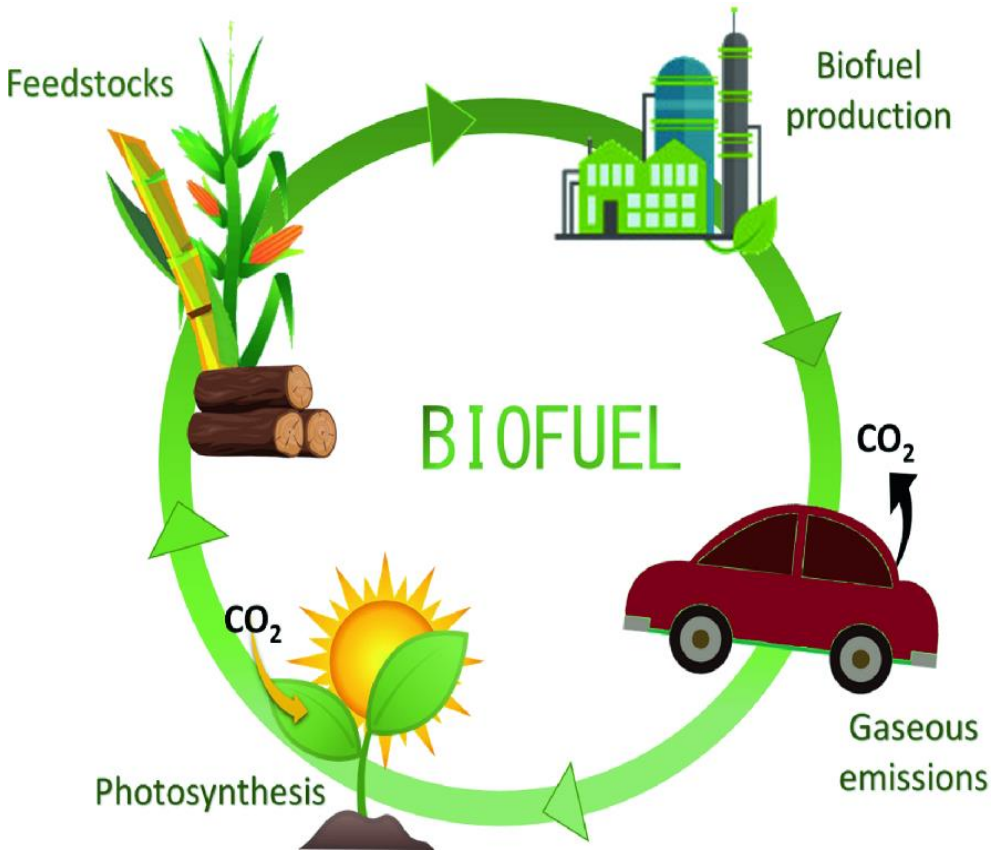
Biofuels is a term used to refer to all fuels produced from biomass, i.e. waste from plant organisms available in the present environment (Ali et al. 2020; Nalule 2020) as shown in Figure 1.1. Biofuel ingredients usually come from oilseeds, corn, sugarcane, wheat, cassava or cassava, soybeans or soybeans, eucalyptus, palm trees, sunflowers, pine and algal oil (Olanrele et al. 2020; Koçar and Civaş 2013; Cho et al. 2011; Voloshin et al. 2016; Olguín 2012; Li et al. 2008; Wahlen et al. 2013).

The use of the prefix "bio" indicates that the fuel is renewable and, in theory, its use results in less environmental impact, that is, it favours sustainable consumption.

A positive factor in the biofuel production process is that plants, while growing in large fields, tend to absorb carbon dioxide from the environment. However, the energy cost of processing raw materials into biofuels is greater than its benefits.

Figure 1.1

Biofuel



Moreover, in 2010, global production of biofuels reached 105 billion liters, more than 17% more than in 2009 (Hannon et al. 2008; Griffiths et al. 2021; Balat and Balat 2009). Biofuels contribute 2.7% of the world's fuel used in road transport, especially ethanol and biodiesel (Liaquat et al. 2010). Global production of ethanol fuel reached 86 billion liters in 2010. The United States and Brazil were the top producers, together contributing 90 percent of global production. The world's largest producer of biodiesel is the European Union, which contributed 53% of total biodiesel production in 2010 (Shalaby 2013).

At the beginning of this century, the United States announced a 15-year plan to produce 150 billion liters of ethanol using wheat, some plants and wood, after it relied on corn for its ethanol production, which produces 45% of global production (Menon and Rao 2012).

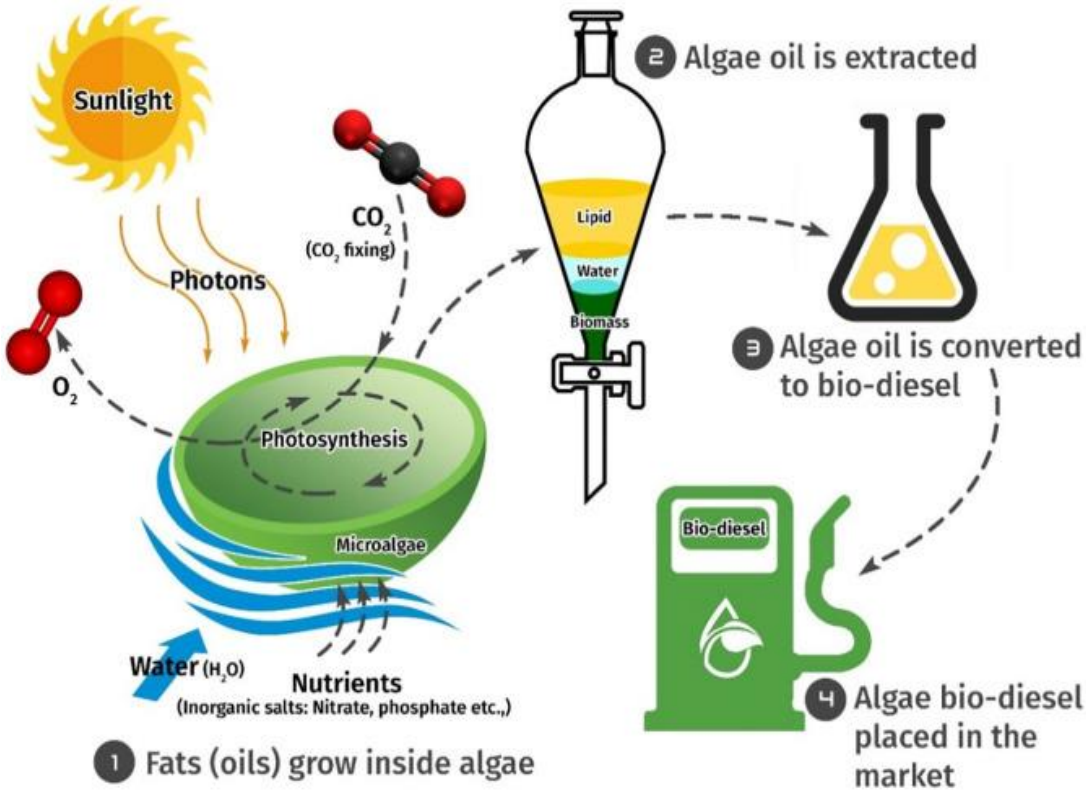
With the exception of ethanol produced by Brazil from sugar cane, whose production costs are considered the lowest among the countries producing biofuels.

This type of fuel cannot currently compete with fossil fuels without obtaining government subsidies, special facilities, and tax incentives that enabled it to survive commercially in many cases (Popp et al. 2014). As for biodiesel production, America and Brazil produce it from soybeans, and the European Union countries from rapeseed (Popp et al. 2014).

Furthermore, the use of land to grow energy crops, and the transformation of agricultural fields producing food crops for human or animal consumption into fields for the production of biofuels, causes an imbalance in global agricultural diversity, the uprooting of many forests and natural reserves, an increase in soil erosion rates, and the consumption of huge amounts of water. Some studies estimate that producing one liter of biofuel requires 5,000 liters of water, and that producing 13 liters of ethanol needs, for example, 231 kilograms of corn (Groom et al. 2008).

Figure 1.2

*Algae biodiesel productio*n



Biofuels cause a high level of water and air pollution caused by the large quantities of agricultural pesticides and fertilizers required to grow energy crops, and will affect and exhaust soil quality (Pimentel et al. 2008).

Other restrictions include petroleum discoveries in different regions of the world, especially in the Middle East, which play an important role in rearranging the current and future energy system, and formulating it in the direction of reconsidering policies to expand or accelerate the production of biofuels and energy alternatives in general.

Main Advantages of Biofuels

Biofuels have many advantages (Van Ginkel et al. 2015; Jumbe et al. 2009; De Gorter et al. 2013; Peskett et al. 2007; Dahman et al. 2019) such as

- It is an environmental fuel
- Biofuel contains 11 percent of oxygen and no sulfur.
- Its use can extend the life of diesel engines, as it contains more lubricant than petroleum.
- Biodiesel is safe in terms of control and transportation, as its biodegradation is similar to sugar, and its toxicity is 10 times lower than that of table salt.
- The success of this technology has been proven experimentally, as it was used to drive vehicles for 30 million miles in the United States of America alone.
- Its combustion does not produce unpleasant odors such as those produced by burning fossil fuels, and thus eliminates a form of pollution.

Disadvantages of Biofuels

There are disadvantages for biofuels as shown in Figure 1.3 (Deora, et al. 2021; Simionescu et al. 2017).

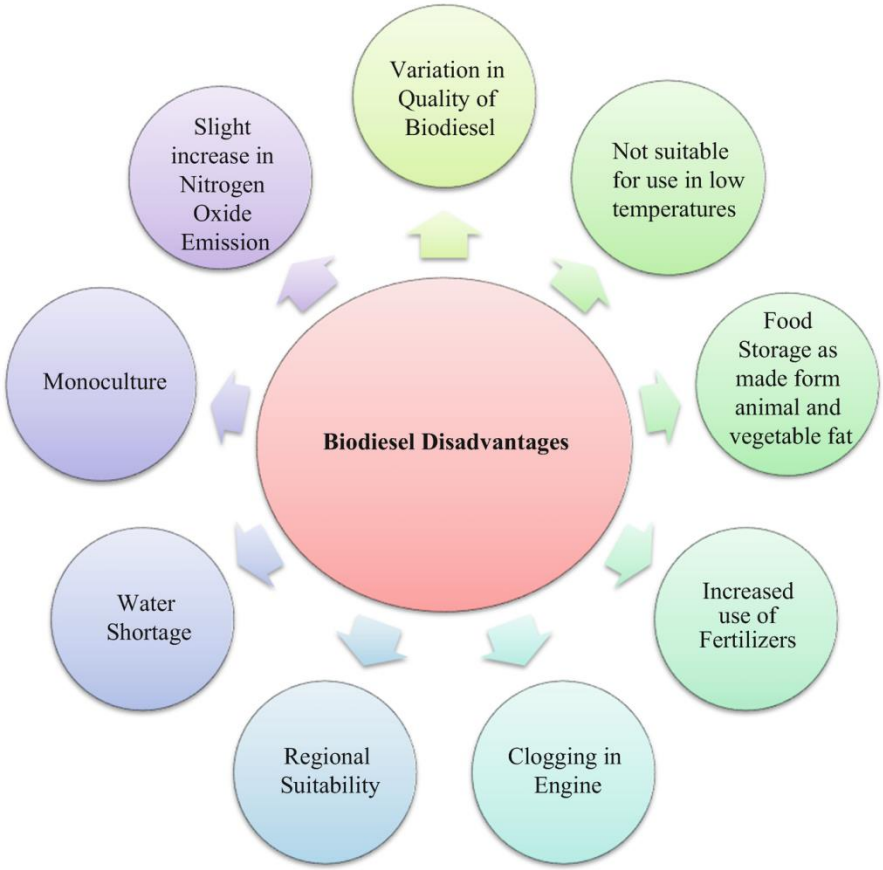
- With all the benefits associated with biofuels, its production in the current market is very expensive, as of now the interest and capital investment that is invested in biofuel production is rather low but can match the demand. If the demand is increased then the increase in supply will be practical Long term and potentially very costly, this

drawback still prevents the use of biofuels from becoming more common.

- Carbon footprint of biofuels is lower than that of conventional fuels when combusted. However, the process by which they are produced makes up for this, as production largely depends on a lot of water and oil. Large industries dedicated to biofuel production are known to emit large amounts of emissions and cause water pollution on a small scale as well, unless more efficient production methods are put in place the overall carbon emissions will not have a significant impact, and it causes an increase in NO_x Nitrogen. Water use: Large amounts of water are required to irrigate biofuel crops and this may put pressure on local and regional water resources if not managed wisely.
- Production of biofuels consisting mostly of hydrogen, carbon and carbon dioxide that contributes to global warming. It is true that biofuels produce fewer greenhouse gas emissions than fossil fuels, but this only slows down global warming and does not stop or reverse it. Thus, biofuels may be able to help alleviate our energy needs but they will not solve all of our problems, as they can only serve as short-term alternatives when we invest in other technologies.
- Biofuels are less suitable for use at lower temperatures, they are more likely to attract moisture than fossil diesel, which causes problems in cold weather, and they increase the growth of microbes in the engine that clog engine filters.

Figure 1.3

Disadvantages of Biofuels



Purpose of the Study

The aim of this study is to evaluate impact of the fatty acid profile on the prediction of CN of biodiesel. To this aim, 6 empirical models were, namely, linear model, linear+interaction model, linear+squared model, full quadratic model, feedforward artificial neural network (multilayer perceptron (MLP)) and radial basis function are used to identify the most relevant parameters for prediction of CN of fuel. For this purpose, 135 different type of biodiesel with 14 methyl esters of the following fatty acids: Capric acid (C10:00), Lauric acid (C12:00), Myristic acid (C14:00), Palmitic acid (C16:00), Palmitoleic acid (C16:01), Stearic acid (C18:00), Oleic acid (C18:01), Linoleic acid (C18:02), Linolenic acid (C18:03), Arachidic acid (C20:00), Paullinic acid (C20:01), Behenic acid (C22:00), Erucic acid (C22:01), and Lignoceric acid (C24:00) were used for developing the proposed

model. To this aim, 36 models were developed with various input parameter of combinations.

Significance of the Study

It is becoming more and more important to improve the precision in the prediction of properties of biodiesel mainly cetane number (CN). The CN is a reference value by which the readiness of the fuel for spontaneous combustion, under pressure and in the presence of oxygen, can be indicated. The cetane number refers to cetane (hexadecane). This hydrocarbon ignites easily under pressure and in the presence of oxygen. Therefore, cetane is used as a reference fuel to determine the cetane number of diesel fuel as a measure of self-ignition.

Generally, no detailed study about finding the important parameters those affect the predicting of CN, according to authors' review.

CHAPTER II

Literature review

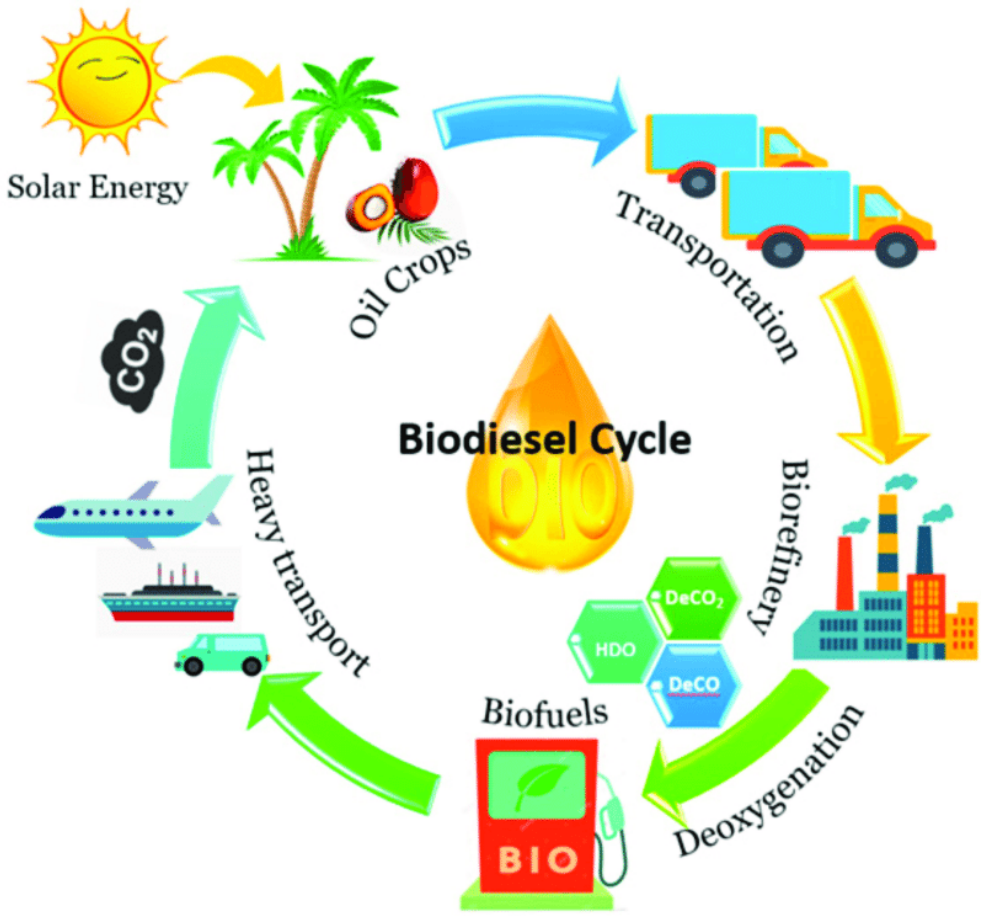
Main characteristics of biodiesel, empirical models used to estimate the properties of biodiesel are given in this chapter.

Biodiesel

Biodiesel is a clean-burning alternative fuel (Demirbas 2008). It is derived from local and renewable sources such as vegetable oils or animal fats (Figure 2.1) (Singh et al. 2020). This type of fuel does not usually contain petroleum, but it is possible to create a blend of biodiesel by mixing it with petroleum diesel (Elkelawy et al. 2019, Hosamani and Katti 2018).

Figure 2.1

Biodiesel cycle

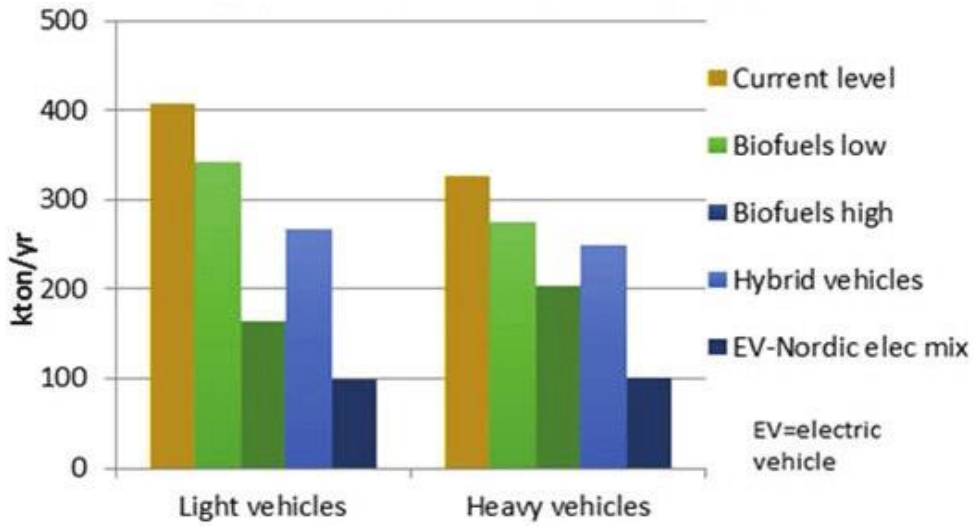


This type of fuel is considered completely safe because it is free of any toxic substance, and it is rapidly degradable (Hughes et al. 2020). Thus, the effect of releasing biodiesel into the environment in small quantities is less than that of releasing the same amount of ordinary fuel or oil. However, getting rid of it in larger quantities is still generally harmful to the environment. Moreover, it is not expensive because it is made from cheap raw materials: fats, cooking oil and grease (Gebremariam and Marchetti 2018). These items have no other use except for dumping in the garbage. Additionally, it is almost ready for use without any major modifications, which significantly reduces cost. It can be used in any model of diesel vehicles without any need for a new type of engine (Noor et al. 2020). Biodiesel improves lubrication and conductivity, making them good for mechanical functions and the smooth running of vehicle engines (Dey et al. 2021).

In the end, it has many advantages over diesel fuel such as inherent lubricity, non-toxic and biodegradable, free of sulfur and aromatics, higher cetane number and flashpoint, reducing greenhouse gas emissions (Figure 2.2) and lower exhaust emissions excepting higher NO_x emissions (Sharma and Murugan 2017; Zhou et al. 2017).

Figure 2.2

CO2 emissions for road transport



Biodiesel and conventional diesel blends are commonly distributed for use in the diesel fuel retail market. Much of the world uses a system known as the "B" factor to determine the amount of biodiesel in any fuel mixture. For example, 100% biodiesel is referred to as B100, 20% biofuel, 80% petrodiesel labeled B20, 5% biofuel, 95% petrodiesel labeled B5 and 2% biofuel, 98% petrodiesel labeled B2.

Biodiesel is commonly produced by trans-esterification of vegetable oil or animal fat feedstock, and other non-edible raw materials such as frying oil, etc (Elgharbawy et al. 2021). There are several methods for carrying out this transesterification reaction including common batch process, heterogeneous catalysts, supercritical processes, ultrasound methods, and even microwave methods (Elgharbawy et al. 2021).

Chemically, esterification biodiesel comprises a mixture of mono-alkyl esters of long-chain fatty acids. The most common form uses methanol to produce methyl esters biodiesel because it is the cheapest alcohol available, although ethanol can be used to produce ethyl ester biodiesel and higher alcohols such as isopropanol and butanol have been used (Mamat et al. 2019). The use of alcohols with higher molecular weights improves the cold flow properties of the resulting ester, at the expense of a less efficient esterification reaction.

A fat transesterification process is used to convert the oil into the desired esters base. Any free fatty acids in the essential oil are either converted into soap and removed from the process, or esterified (to produce more biodiesel) using an acid catalyst. After this processing, unlike straight vegetable oil, biodiesel has very similar combustion properties to petroleum diesel fuel, and can replace it in most current uses. The methanol used in most biodiesel production processes is manufactured using fossil fuel inputs. However, there are sources of renewable methanol made using carbon dioxide or biomass as a feedstock, making their production processes free of fossil fuels.

Main Characteristics of Biodiesel

As mentioned before, biodiesel is derived from vegetable oils or animal fats by the transesterification process, and the resulting fuel is used as an alternative to petroleum-based fuels in diesel engines.

Vegetable oils and animal fats have high densities and viscosities, which constitutes an obstacle that prevents their use in internal combustion engines directly

(Singh et al. 2020). Therefore, it is resorted to treating these materials by the transesterification method using short-chain alcohols (especially methanol), and this process results in methyl esters of fatty acids (Salaheldeen et al. 2021). Therefore, it is necessary to know the physical properties of biodiesel fuel as a function of temperature. This can be achieved by developing tight mathematical models to estimate these properties or by measuring directly. This is necessary for the engineering study of combustion processes in engines, especially when using computers in the design, simulation, fit, control processes and so on. Researchers have paid a lot of attention to modelling the combustion process of biodiesel to use it optimally by understanding the principles. Besides, they paid a lot of attention to mix the biodiesel with diesel increase the performance of diesel engine and reduce the demand for petroleum fuels. Moreover, there is an important environmental reason behind the use of biodiesel. The previous studies showed that the use of this fuel reduces the emissions resulting from combustion of unburned organic compounds, suspended matter and carbon monoxide.

In order to obtain accurate estimates of the combustion process of alternative fuels, it is necessary first to accurately estimate the physical properties, mainly in the cases of atomization, spraying and combustion in the combustion chamber of the engine.

Generally, density and viscosity are important physical properties that help to define the quality of fuels, besides being widely used in models of combustion, as well as for the design, operation, and control of processes (Hoang 2019). Density and viscosity are associated to the atomization process of fuels during its injection into the combustion chamber (Hoang and Le 2019).

Furthermore, cetane number (CN) is one of the main indicators that characterize biodiesel fuel (Kaisan et al. 2017). The CN is an indicator of the quality of combustion of fuels during the ignition process (Schweidtmann et al. 2020). The cetane number characterizes the flammability of the fuel (Labeckas et al. 2017). The higher this indicator, the less time passes from the injection of fuel into the working cylinder to the beginning of its combustion, and, accordingly, the shorter the engine warm-up time (Labeckas et al. 2017).

The cetane number is a reference value by which the readiness of the fuel for spontaneous combustion, under pressure and in the presence of oxygen, can be indicated (Nabi et al. 2015). The cetane number refers to cetane (hexadecane). This

is a hydrocarbon that ignites easily under pressure and in the presence of oxygen. Therefore, cetane is used as a reference fuel to determine the cetane number of diesel fuel as a measure of self-ignition. The behavior of the fuel is compared to that of cetane. A cetane number of 100 is mean that the fuel behaves like 100% cetane. However, there is no need for cetane to be present in the fuel: the cetane number is a reference value that says something about the behavior of the fuel.

In general, the higher the cetane number, the better to run a diesel engine on it. Several scientific studies have been analyzed the effect of cetane number of the performance of diesel engine (Chukwuezie et al. 2017; İçıngür and Altiparmak 2003; Ahmed and Chaichan 2012; Li et al. 2014; Musthafa 2017; Labeckas et al. 2017). For instance, İçıngür and Altiparmak (2003) investigated the effect of various fuel cetane numbers on the performance of the diesel engine. They found that the performance of engine increased when the cetane number is above than 54.5. Ahmed and Chaichan (2012) studied the effect of adding the 2-ethylhexyl nitrate on the cetane number of fuel diesel. Li et al. (2014) used three cetane number improvers, which added to the biodiesel-methanol blends with various ratios to improve the engine performance.

Empirical Models

Many models and techniques are such as machine learning models and mathematical models are used as alternative tools to descript a complex system. They are utilized in a wide variety of applications.

Numerous scientific researchers have used various empirical models to predict the properties of biodiesel. For example, Freitas et al. (2011) used different models for predicting the viscosity of biodiesel at various temperatures. Pratas et al. (2011) proposed a methodology based on the Kay's mixing rule and the group contribution method for predicting the density of ten samples of biodiesel as a function of temperature. Ramírez-Verduzco et al. (2012) developed empirical correlations to predict the cetane number, density, viscosity, and higher heating value (HHV) of biodiesel from its chemical composition. Pilot-Rodríguez et al. (2013) predicted the cetane number of biodiesel using artificial neural networks. The authors used an array of 11:5:1, eleven entries for the composition of methyl esters in biodiesel, five neurons in the hidden layer, and one variable for the output that corresponds to the cetane number. Meng et al. (2014) obtained a correlation

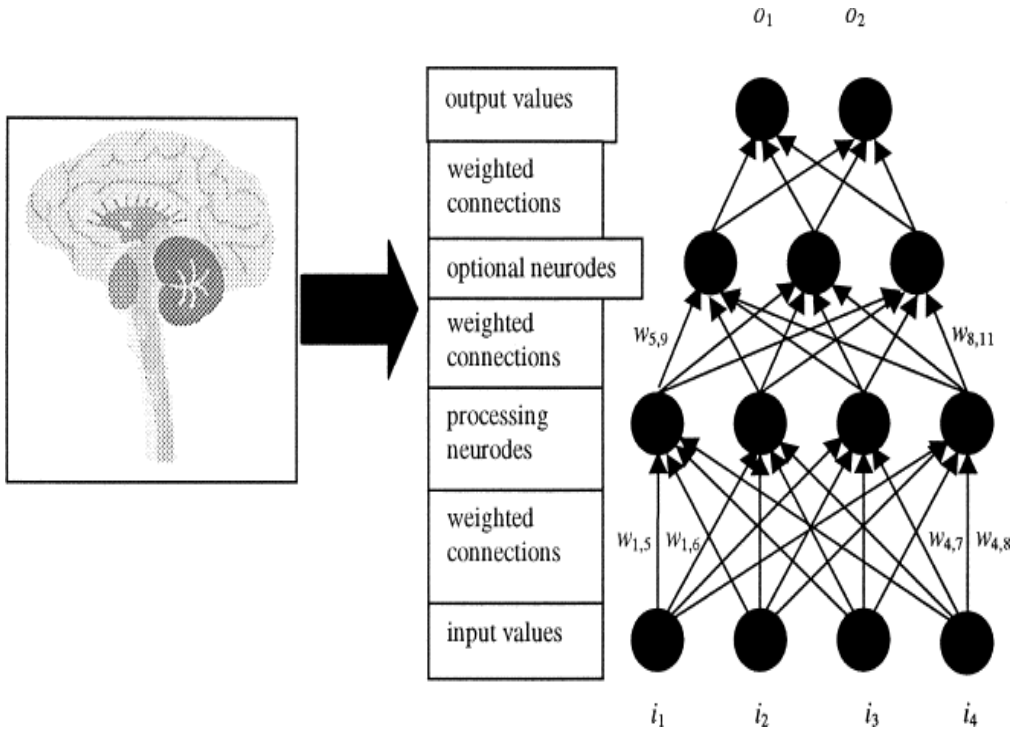
coefficient of 0.9772 on the prediction of the kinematic viscosity at 313 K. Balabin et al. (2011) showed that their developed artificial neural network had a small mean squared error with respect to other models. Saldana et al. (2012) reported different models of artificial neural network with correlation coefficient between 0.985 and 0.995. Miraboutalebi et al. (2016) developed and compared the random forest and ANN models to estimate CN based on the fatty acid methyl esters content of biodiesel. Tong et al. (2011) used multiple linear regression model (MLRM) to correlate CN and fatty acid methyl ester (FAME) of biodiesel. Hosseinpour et al. (2016) utilized partial least square (PLS) based on ANN was also used to estimate CN from its FAMEs. In another study, the effect of biodiesel composition on Cetane number was defined through straight-chain saturated factor (SCSF) and modified the degree of unsaturation (DUm) comparing 9 different biodiesel fuels (Mishra et al. 2016). The regression coefficient of 0.95 and average absolute deviation of 1.63 was reported in this study.

Artificial Neural Network Models

The ANN is a simulation technique for modelling a complex system, see Figure 2.1, (Kalogirou 2003; Kalogirou 2011). It has been utilized in various areas of science and engineering. The scientific researchers have developed many types of ANNs such as of which the feed-forward neural network (FFNN) or multilayer perceptron (MLP) is one of the most popular ANNs. The node numbers in the input and output layers are estimated by the nature of the problem).

Figure 2.3

ANN model



In general, there are three main layers including input layer, hidden layer and output layer in MLP. The number of hidden layer is estimated based on the trial and error method. The backpropagation algorithm is widely used as a learning algorithm and it is a gradient descent algorithm.

The logistic-sigmoid (*logsig*) and tangent-sigmoid (*tansig*) are used as activation functions whose outputs lie between 0 and 1 and are defined as

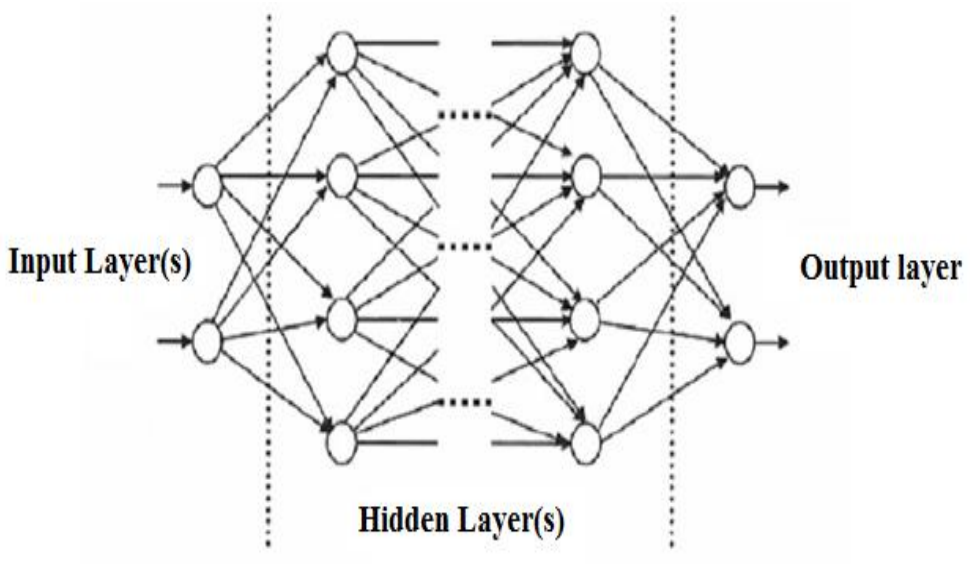
$$logsig = \frac{1}{1 + e^{-x}} \tag{2.1}$$

$$tansig = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2.2}$$

Figure 2.2 shows the schematic diagram of typical multi-layer feed forward neural network architecture.

Figure 2.4

Multi-layer feed forward network model



Another type of ANN is radial basis function (RBFNN). RBFNN is one of the most popular kinds of ANNs that utilizes radial basis functions as activation functions. It is a type of FFNN composed of three layers (input, hidden and output layers) (Barati-Harooni and Najafi-Marghmaleki 2016). Gaussian function is widely used as the transfer function in computational units. In addition, the training of the RBFNN model is terminated once the calculated error reached the desired values or number of training iterations. The number of nodes of input layer is identical to the number of model inputs.

Mathematical Model (ME)

Several mathematical models are utilized to predict the properties of biodiesel such as response surface methodology (RSM). RSM is applied for developing, improving, and optimizing complex processes (Okpalaeke et al. 2020; Betiku et al. 2014). This method has some benefits like lessening the number of measurements and bringing analytically results.

Based on the actual data, regression analysis was carried out by the following model:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i}^{n-1} \sum_{i=i+1}^{n} \beta_{ij} x_i x_j \qquad (2.3)$$

where Y is the predicted response, β_0 a constant, β_i the linear coefficient, β_{ii} the squared coefficient, and β_{ij} the cross-product coefficient, n is the number of factors, x_i and x_j are the independent variables.

CHAPTER III
Material and Method

This chapter provides information about the data collection and analysis procedures as well as how the findings are analysed.

Data Collections

The value of CN and chemical compositions of various type of biodiesel are collected from the previous studies (Gopinath et al. 2009; Tong et al. 2011; Piloto-Rodríguez et al. 2013; Azam et al. 2005; Winayanuwattikun et al. 2008). Name of the selected biodiesel and the fatty acid composition of 135 biodiesel including 14 methyl esters of the following fatty acids: Capric acid (C10:00), Lauric acid (C12:00), Myristic acid (C14:00), Palmitic acid (C16:00), Palmitoleic acid (C16:01), Stearic acid (C18:00), Oleic acid (C18:01), Linoleic acid (C18:02), Linolenic acid (C18:03), Arachidic acid (C20:00), Paullinic acid (C20:01), Behenic acid (C22:00), Erucic acid (C22:01), and Lignoceric acid (C24:00), respectively are shown in appendix A.

In this study, the estimating values of the sum of the saturated ($\sum SFAMs$), monounsaturated ($\sum MUFAMs$), polyunsaturated ($\sum PUFAMs$), were estimated using the below equations.

$$\sum MUFAMs = \sum wt\%Cxx{:}\,1 \tag{3.1}$$

$$\sum PUFAMs = \sum wt\%Cxx{:}\,2 + \sum wt\%Cxx{:}\,3 \tag{3.2}$$

$$\sum SFAMs = \sum wt\%Cxx{:}\,00 \tag{3.3}$$

The summary statistics of the independent variables, which are considered as input and dependent variables (output), are given in Table 3.1.

Table 3.1

Models with different input combinations

Variable	Mean	Standard deviation	Minimum	Maximum
C10:00	0.821	8.613	0	100
C12:00	5.18	18.54	0	100
C14:00	3.27	11.83	0	100
C16:00	13.09	13.87	0	100
C16:01	1.164	8.712	0	100
C18:00	7.89	13.07	0	100
C18:01	34.99	22.43	0	100
C18:02	22.94	22.17	0	100
C18:03	4.07	12.74	0	100
C20:00	1.752	9.404	0	100
C20:01	0.975	8.651	0	100
C22:00	0.959	8.619	0	100
C22:01	1.27	9.621	0	100
C24:00	1.22	9.789	0	100
$\sum MUFAMs$	38.4	23.92	0	100
$\sum PUFAMs$	27.01	25.49	0	100
$\sum SFAMs$	34.19	28.74	0	118.99
CN	54.257	10.526	22.7	100

ANN models

In this study, TRAINLM was utilized as a training function. In addition, Mean squared error (MSE) is estimated to find the best performance of the training algorithm. The declining gradient of the back-propagation algorithm was used to reduce the value of MSE between the actual and estimated output. Moreover, Gaussian function is used as the transfer function in computational units for RBFNN. Figures 3.1 and 3.2 illustrate the explanation process of the proposed MFFNN and RBFNN methods. In this study, the data are divided into training and testing groups and the results by the models are compared with each. 75% of the data comprise the training part and the other 25% goes into the testing part. A series of models are examined to estimate the optimum number of hidden layers (HL), number of neurons (NN) and transfer function (TF) for the MFFNN model.

Figure 3.1

The proposed algorithm of predicting CN using MFFNN

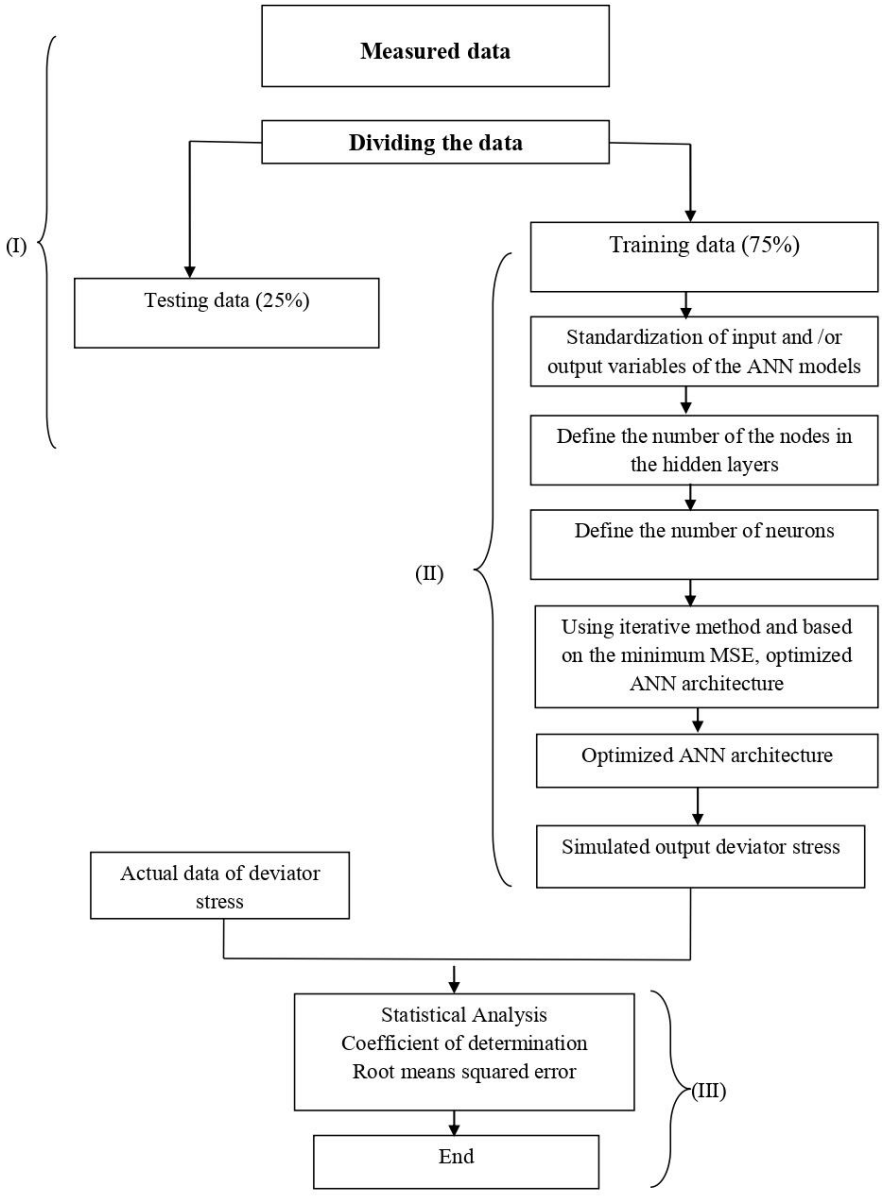
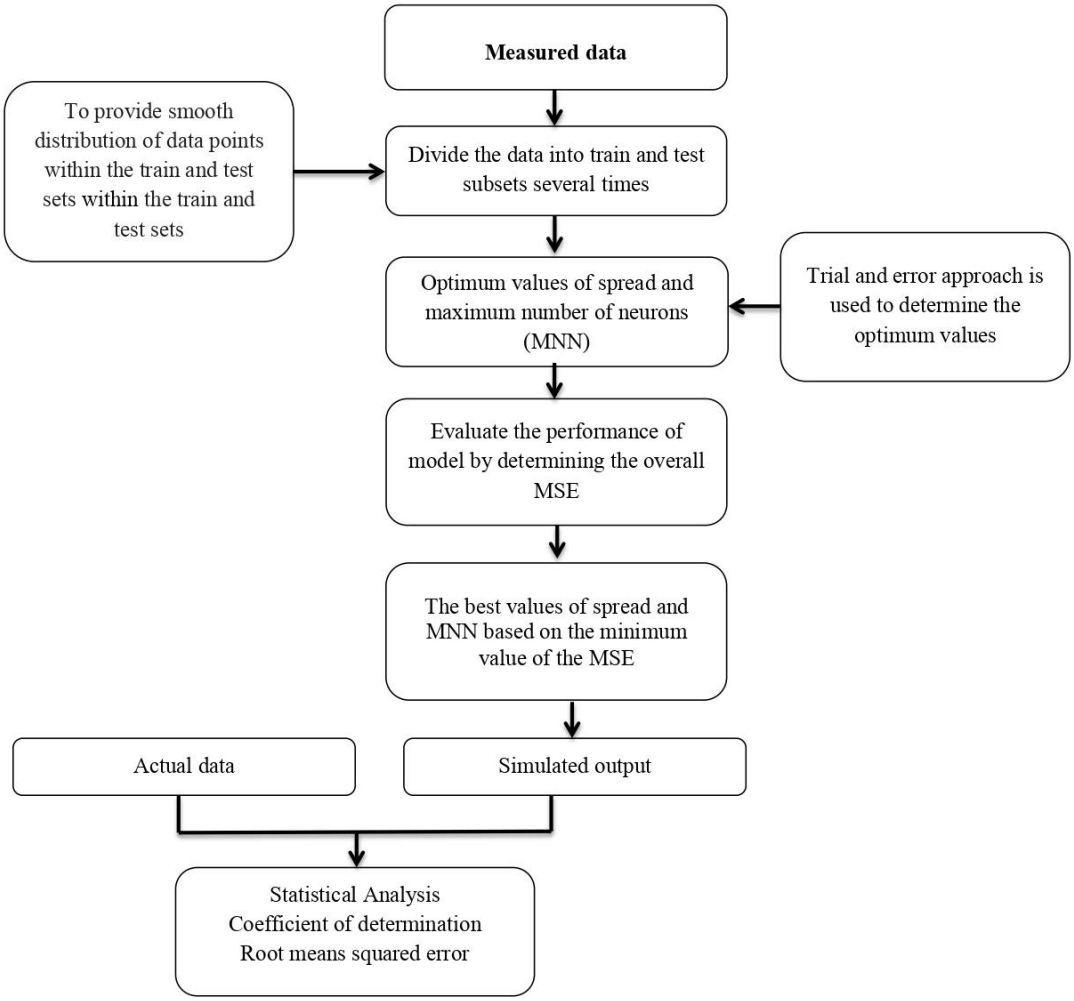


Figure 3.2

The proposed algorithm of predicting CN using RBFNN



ME Models

The response surface regression model was used to study the response pattern and to determine the optimum combination of variables. The Minitab statistical software 17 was used for the regression and graphical analysis of the data.

Generally, the following model carried out regression analysis:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i}^{n-1} \sum_{i=i+1}^{n} \beta_{ij} x_i x_j \qquad (3.4)$$

where Y is the predicted response, β_0 a constant, β_i the linear coefficient, β_{ii} the squared coefficient, and β_{ij} the cross-product coefficient, n is the number of factors, x_i and x_j are the independent variables.

Model Performance Criteria

The performance of the proposed models were evaluated based on the following equations

$$R - squared = 1 - \frac{\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2}{\sum_{i=1}^{n}\left(a_{p,i} - a_{a,ave}\right)^2} \quad (3.5)$$

$$Mean\ squared\ error = \frac{1}{n}\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2 \quad (3.6)$$

$$Root\ mean\ squared\ error = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2} \quad (3.7)$$

Proposed Models

Seven conditions were considered in the model development of empirical models with different input combinations and are utilized to train the model to identify the best combination of inputs to estimate the CN of biodiesel. In this work, several empirical models with various possible combinations of the used inputs were built as shown in Table 3.2. Then they were trained respectively and then the performance of these models was estimated.

Table 3.2

Models with different input combinations

Model Name	**Combination of input**
Model#1	$\sum MUFAMs$
Model#2	$\sum PUFAMs$
Model#3	$\sum SFAMs$
Model#4	$\sum MUFAMs$,$\sum PUFAMs$
Model#5	$\sum MUFAMs$, $\sum SFAMs$
Model#6	$\sum PUFAMs$,$\sum SFAMs$
Model#7	$\sum MUFAMs$, $\sum PUFAMs$,$\sum SFAMs$

CHAPTER IV
Findings and Discussion

This chapter presents the findings based on the collected data. It should be noted that a series of models were examined to estimate the optimum models. , it was found that *tansig* was chosen as the best TF for MFFNN model

Evaluate the Influence of Input Variables

In the first case (parameter selection for one input), 12 models with one input were developed to find the most influencing input parameters for estimating the CN. Table 4.1 shows the value of the R-squared and RMSE for all developed models. Additionally, the mathematical equation for models (ME#1-ME#6) can be expressed as shown below.

$$CN = 52.77 + 0.0386 \cdot \sum MUFAMs \quad (4.1)$$

$$CN = 56.61 - 0.226 \cdot \sum MUFAMs + 0.00309 \cdot \left(\sum MUFAMs\right)^2 \quad (4.2)$$

$$CN = 63.146 + 03269 \cdot \sum PUFAMs \quad (4.3)$$

$$CN = 63.404 - 0.3563 \cdot \sum PUFAMs + 0.00392 \cdot \left(\sum PUFAMs\right)^2 \quad (4.4)$$

$$CN = 46.05 + 0.2445 \cdot \sum SFAMs \quad (4.5)$$

$$CN = 45.11 - 0.3082 \cdot \sum SFAMs + 0.000631 \cdot \left(\sum SFAMs\right)^2 \quad (4.6)$$

It is found that RBFNN#2 gave the best performance followed by ENN, FFNN, and CFNN for estimating the input. Moreover, it is observed that RBFNN#2 gave the highest R^2 value with a value of 0.6459 followed by ME#4 with a value of 0.6277. Furthermore, it is noticed that the lowest RMSE value of 6.2417 is recorded for RBFNN#2 followed by ME#4 with RMSE value of 6.3992.

Table 4.1

Performance of the proposed models with one input

Model Name	Input	R^2	RMSE
MLP#1	$\sum MUFAMs$	0.0153	10.4066
MLP#2	$\sum PUFAMs$	0.6169	6.5181
MLP#3	$\sum SFAMs$	0.4181	8.0070
RBFNN#1	$\sum MUFAMs$	0.2987	8.8062
RBFNN#2	$\sum MUFAMs$	0.6459	6.2417
RBFNN#3	$\sum MUFAMs$	0.4579	7.7257
ME#1	$\sum MUFAMs$	0.0078	10.4462
ME#2	$\sum MUFAMs$	0.0565	10.1863
ME#3	$\sum PUFAMs$	0.6270	6.4048
ME#4	$\sum PUFAMs$	0.6277	6.3992
ME#5	$\sum SFAMs$	0.4195	7.9899
ME#6	$\sum SFAMs$	0.0048	7.9735

In the second case (parameter selection for two inputs), 18 models with two combination of parameters were proposed as shown in Table 4.2. Eqs. (4.7) –(4.18) represent the expression of the mathematical equation for models (ME#7-ME#18)

$$CN = 32.27 + 0.257 \sum MUFAMs + 0.3604 \sum SFAMs \tag{4.7}$$

$$CN = 32.82 + 0.304 \sum MUFAMs + 0.248 \sum SFAMs - 0.0004 \left(\sum MUFAMs\right)^2 + 0.00119 \left(\sum SFAMs\right)^2 \tag{4.8}$$

$$CN = 31.99 + 0.2883 \sum MUFAMs + 0.3797 \sum SFAMs - 0.001653 \sum MUFAMs \sum SFAMs \tag{4.9}$$

$$CN = 29.47 - 0.388 \cdot \sum MUFAMs + 0.491 \sum SFAMs - 0.00082 \left(\sum MUFAMs\right)^2 - 0.00088 \left(\sum SFAMs\right)^2 - 0.00346 \sum MUFAMs \sum SFAMs \quad (4.10)$$

$$CN = 68.07 - 0.1028 \sum MUFAMs - 0.3625 \sum PUFAMs \quad (4.11)$$

$$CN = 69.40 - 0.2721 \sum MUFAMs - 0.2141 \sum PUFAMs + 0.001834 \left(\sum MUFAMs\right)^2 - 00019 \left(\sum PUFAMs\right)^2 \quad (4.12)$$

$$CN = 68.11 - 0.1124 \sum MUFAMs - 0.3808 \sum PUFAMs - 0.001 \sum MUFAMs \sum PUFAMs \quad (4.13)$$

$$CN = 69.56 - 0.2757 \cdot \sum MUFAMs - 0.264 \sum PUFAMs + 0.001835 \left(\sum MUFAMs\right)^2 - 0.00141 \left(\sum PUFAMs\right)^2 + 0.00082 \sum MUFAMs \sum PUFAMs \quad (4.14)$$

$$CN = 57.89 - 0.2599 \sum PUFAMs + 0.1025 \sum SFAMs \quad (4.15)$$

$$CN = 59.05 - 0.1644 \sum PUFAMs - 0.0334 \sum SFAMs - 0.001134 \left(\sum PUFAMs\right)^2 + 0001398 \left(\sum SFAMs\right)^2 \quad (4.16)$$

$$CN = 57.77 - 0.2654 \sum PUFAMs + 0.1021 \sum SFAMs + 0.00056 \sum PUFAMs \sum SFAMs \quad (4.17)$$

$$CN = 60.45 - 0.268 \cdot \sum PUFAMs - 0.097 \sum SFAMs + 0.0045 \left(\sum PUFAMs\right)^2 + 0.0019 \left(\sum SFAMs\right)^2 + 0.00278 \sum PUFAMs \sum SFAMs \quad (4.18)$$

The analysis show that ME#16 with a combination of [$\sum PUFAMs$, $\sum SFAMs$] has the highest value of R^2, while RBFNN#5 has the lowest value of RMSE with a value of 5.3128.

Table 4.2

Performance of the proposed models with two inputs

Model Name	Input	R^2	RMSE
MLP#4	$\sum MUFAMs,\ \sum SFAMs$	0.7079	5.7526
MLP#5	$\sum MUFAMs,\ \sum PUFAMs$	0.6707	6.0516
MLP#6	$\sum PUFAMs,\ \sum SFAMs$	0.6264	6.4513
RBFNN#4	$\sum MUFAMs,\ \sum SFAMs$	0.6678	6.0784
RBFNN#5	$\sum MUFAMs,\ \sum PUFAMs$	0.7528	5.3128
RBFNN#6	$\sum PUFAMs,\ \sum SFAMs$	0.6711	6.0644
ME#7	$\sum MUFAMs,\ \sum SFAMs$	0.7001	5.7841
ME#8	$\sum MUFAMs,\ \sum SFAMs$	0.7086	5.7041
ME#9	$\sum MUFAMs,\ \sum SFAMs$	0.7145	5.6471
ME#10	$\sum MUFAMs,\ \sum SFAMs$	0.7170	5.6213
ME#11	$\sum MUFAMs,\ \sum PUFAMs$	0.7039	5.7467
ME#12	$\sum MUFAMs,\ \sum PUFAMs$	0.7198	5.5932
ME#13	$\sum MUFAMs,\ \sum PUFAMs$	0.7058	5.7288
ME#14	$\sum MUFAMs,\ \sum PUFAMs$	0.7205	5.5860
ME#15	$\sum PUFAMs,\ \sum SFAMs$	0.7040	5.7460
ME#16	$\sum PUFAMs,\ \sum SFAMs$	0.9880	5.5945
ME#17	$\sum PUFAMs,\ \sum SFAMs$	0.7039	5.7472
ME#18	$\sum PUFAMs,\ \sum SFAMs$	0.7221	5.5701

In the third case (parameter selection for three inputs (all inputs), all input variables are utilized as input parameters for the proposed models. It is found that ME#22 with a combination of [$\sum MUFAMs,\ \sum PUFAMs,\ \sum SFAMs$] has shown good prediction accuracy with value of R^2 and RMSE of 0.7294 and 5.4981, respectively as shown in Table 4.3. It should be noted that Eqs. (4.19) –(4.22) represent the expression of the mathematical equation for models (ME#19-ME#22)

$$CN = 64.5 + 0.067 \sum MUFAMs - 0.326 \sum PUFAMs + 0.036 \sum SFAMs \quad (4.19)$$

$$CN = 68.3 - 0.199\sum MUFAMs - 0.216\sum PUFAMs - 0.053\sum SFAMs + 0.00118\left(\sum MUFAMs\right)^2 - 0.00177\left(\sum PUFAMs\right)^2 + 0.00066\left(\sum SFAMs\right)^2 \quad (4.20)$$

$$CN = 67.3 + 0.0.068\sum MUFAMs - 0.380\sum PUFAMs + 0.024\sum SFAMs + 0.00037\sum MUFAMs\sum PUFAMs - 0.001899\sum MUFAMs\sum SFAMs + 0.001333\sum PUFAMs\sum SFAMs \quad (4.21)$$

$$CN = -963 + 22.5\sum MUFAMs + 20.8\sum PUFAMs + 20.4\sum SFAMs + 0.1225\left(\sum MUFAMs\right)^2 - 0.1086\left(\sum PUFAMs\right)^2 + 0.1005\left(\sum SFAMs\right)^2 - 0.1231\sum MUFAMs\sum PUFAMs - 0.225\sum MUFAMs\sum SFAMs - 0.207\sum PUFAMs\sum SFAMs \quad (4.22)$$

Table 4.3

Performance of the proposed models with three inputs

Model Name	Input	R^2	RMSE
MLP#7	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.6491	6.2783
RBFNN#7	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.6986	5.8251
ME#19	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.7041	5.7451
ME#20	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.7215	5.5766
ME#21	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.7213	5.5784
ME#22	$\sum MUFAMs, \sum PUFAMs, \sum SFAMs$	0.7294	5.4981

Comparative Analysis

In this section, the model ranking is explored based on the value of R-squared and RMSE as shown in Tables 4.4 and 4.5 for all proposed models. Based on the value of R-squared, it is found that ME#16 and RBFNN#5 with the combination of $[\sum PUFAMs, \sum SFAMs]$ and $[\sum MUFAMs, \sum PUFAMs]$ respectively, are the best models for estimating the CN. Furthermore, the lowest value of RMSE is recorded for the model of RBFNN#5 with the combination of $[\sum MUFAMs, \sum PUFAMs]$ followed by ME#22 with the combination of $[\sum MUFAMs, \sum PUFAMs, \sum SFAMs]$ as shown in Table 4.5.

Moreover, estimated values of CN using the best-input combination of all developed models are compared with the actual value as shown in Figure 4.1. It should be noted that the number of the selected biodiesel used for testing is shown in Table 4.6. Furthermore, the performance of proposed models is compared with previous modes used in the literature as shown in Table 4.7.

Figure 4.2 shows the comparison between the actual data and estimated data of CN expressed by their relative error. It showed that the values of relative error are with the range of 9.02-13.00, which can be considered an excellent agreement between the measured and estimated data.

Table 4.4

Ranking of proposed models based on R-squared

Model Name	$\sum MUFAMs$	$\sum PUFAMs$	$\sum SFAMs$	R^2	Rank
ME#16		+	+	0.9880	1
RBFNN#5	+	+		0.7528	2
ME#22	+	+	+	0.7294	3
ME#18		+	+	0.7221	4
ME#20	+	+	+	0.7215	5
ME#21	+	+	+	0.7213	6
ME#14	+	+		0.7205	7
ME#12	+	+		0.7198	8
ME#10	+		+	0.7170	9
ME#9	+		+	0.7145	10
ME#8	+		+	0.7086	11
MLP#4	+		+	0.7079	12
ME#13	+	+		0.7058	13
ME#19	+	+	+	0.7041	14
ME#15		+	+	0.7040	15
ME#11	+	+		0.7039	16
ME#17		+	+	0.7039	17
ME#7	+		+	0.7001	18
RBFNN#7	+	+	+	0.6986	19
RBFNN#6		+	+	0.6711	20
MLP#5	+	+		0.6707	21
RBFNN#4	+		+	0.6678	22
MLP#7	+	+	+	0.6491	23
RBFNN#2		+		0.6459	24
ME#4		+		0.6277	25
ME#3		+		0.6270	26
MLP#6		+	+	0.6264	27
MLP#2		+		0.6169	28
RBFNN#3			+	0.4579	29
ME#5			+	0.4195	30
MLP#3			+	0.4181	31
RBFNN#1	+			0.2987	32
ME#2	+			0.0565	33
MLP#1	+			0.0153	34
ME#1	+			0.0078	35
ME#6			+	0.0048	36

Table 4.5

Ranking of proposed models based on RMSE

Model Name	$\sum MUFAMs$	$\sum PUFAMs$	$\sum SFAMs$	RMSE	Rank
RBFNN#5	+	+		5.312777	1
ME#22	+	+	+	5.498141	2
ME#18		+	+	5.570132	3
ME#20	+	+	+	5.576624	4
ME#21	+	+	+	5.578368	5
ME#14	+	+		5.585976	6
ME#12	+	+		5.593154	7
ME#16		+	+	5.594502	8
ME#10	+		+	5.621313	9
ME#9	+		+	5.647074	10
ME#8	+		+	5.704117	11
ME#13	+	+		5.72878	12
ME#19	+	+	+	5.745142	13
ME#15		+	+	5.746025	14
ME#11	+	+		5.746691	15
ME#17		+	+	5.747195	16
MLP#4	+		+	5.752562	17
ME#7	+		+	5.78411	18
RBFNN#7	+	+	+	5.825092	19
MLP#5	+	+		6.051561	20
RBFNN#6		+	+	6.064389	21
RBFNN#4	+		+	6.07844	22
RBFNN#2		+		6.24165	23
MLP#7	+	+	+	6.278317	24
ME#4		+		6.399153	25
ME#3		+		6.40478	26
MLP#6		+	+	6.451321	27
MLP#2		+		6.518062	28
RBFNN#3			+	7.725684	29
ME#6			+	7.973451	30
ME#5			+	7.989883	31
MLP#3			+	8.006996	32
RBFNN#1	+			8.806161	33
ME#2	+			10.1863	34
MLP#1	+			10.40656	35
ME#1	+			10.44623	36

Figure 4.1

Comparison between actual and estimated values

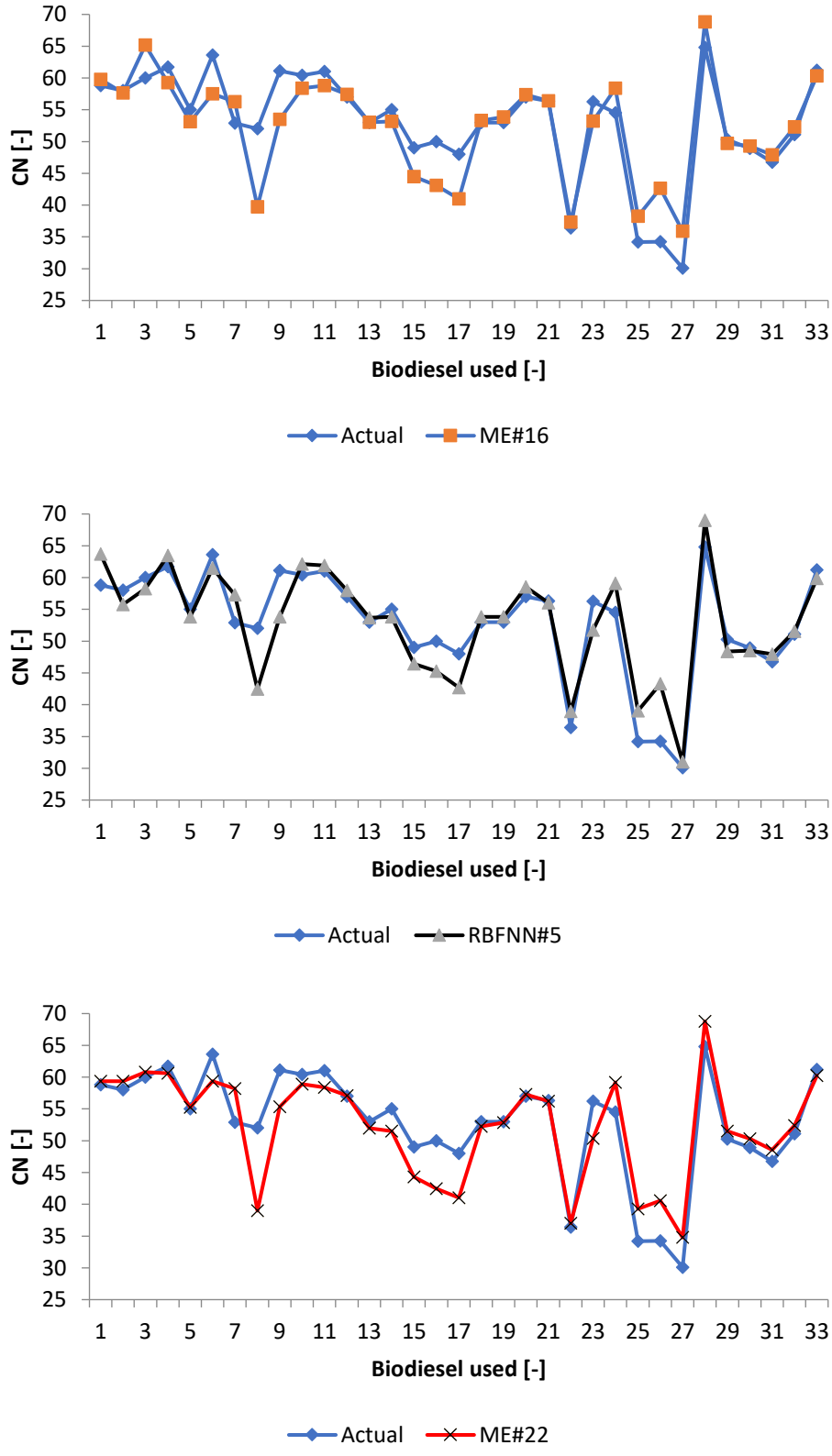


Table 4.6

Name of the selected biodiesel used for testing data

Number of biodiesel	Name of biodiesel
1	Beef Tallow
2	JCt 50:50
3	Coconut
4	Inedible tallow
5	Canola
6	Lard
7	Yellow grease
8	Linseed
9	Wild mustard
10	Waste palm oil
11	Palm
12	Olive
13	Peanut
14	Rape
15	Soybean
16	Sunflower
17	Grape
18	H.O. Sunflower
19	Corn
20	Almond
21	Apocynaceae Ervatamia coronaria Stapf
22	Cannabinaceae Cannabis sativa Linn
23	Combretaceae Terminalia bellirica Roxb
24	Corylaceae Corylus avellana
25	Aleurites moluccana Wild
26	Euphorbia helioscopia Linn
27	Perilla frutescens Britton
28	Litsea glutinosa Robins
29	Magnoliaceae Michelia champaca Linn
30	Rosaceae Princepia utilis Royle
31	Simaroubaceae Quassia indica Nooleboom
32	Sterculaceae Pterygota alata Rbr
33	Ulmaceae Holoptelia integrifolia

Figure 4.2

Comparison between actual and estimated values for tested data

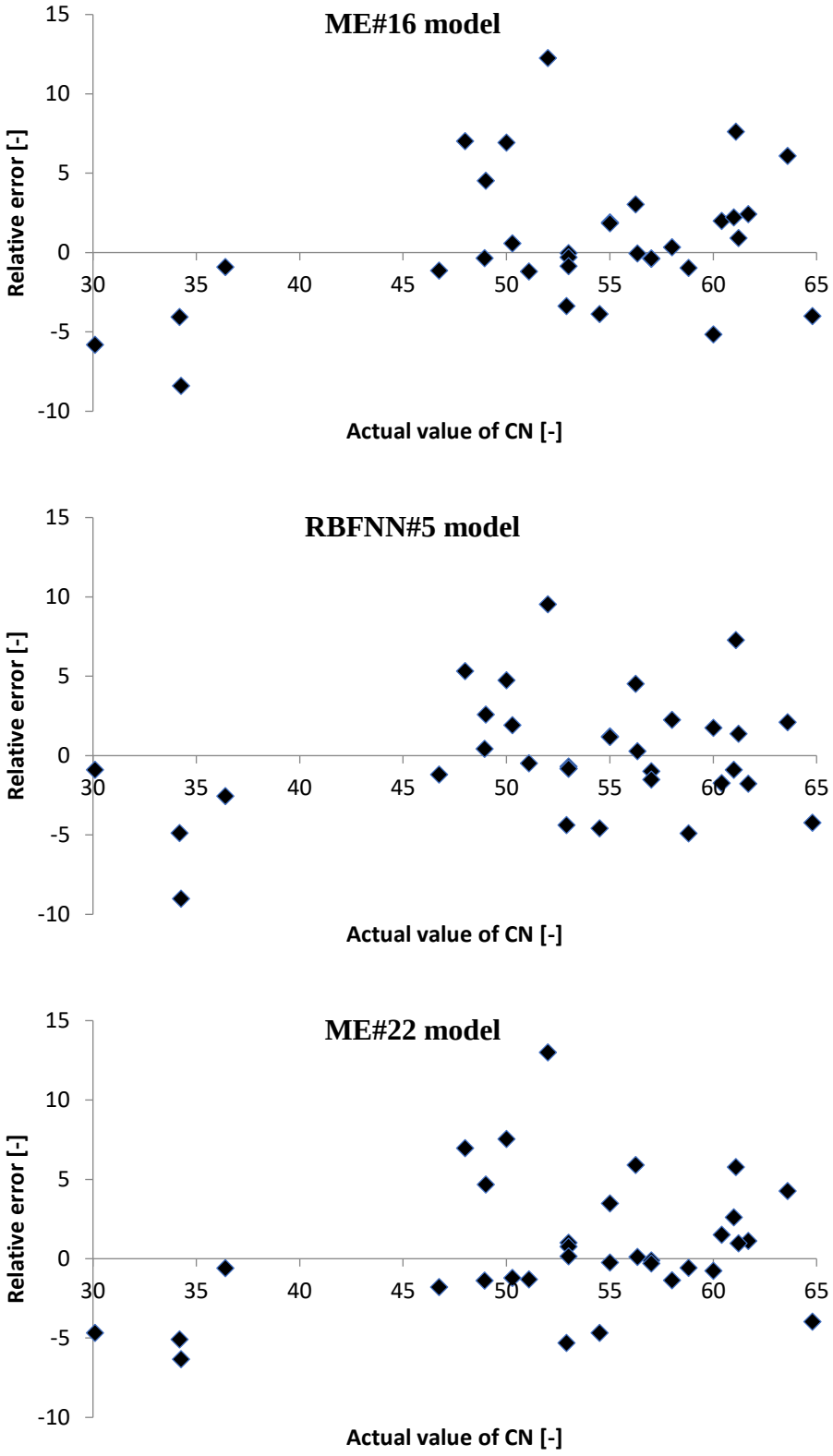


Table 4.7

Comparison of present models with other existing models in the literature

Model used	Characteristics	Statistical performance	Ref.
MLP	One-hidden layer MLP model with gradient descent momentum backpropagation learning algorithm, and tangent sigmoid and linear transfer functions in the hidden and output layers, respectively	Relative error = 3.4%	Ramadhas et al. (2006)
MLP	One-hidden layer MLP model with 5 hidden neurons, backpropagation learning algorithm, and logistic output function	R^2 = 0.9544	Piloto-Rodríguez et al. (2013)
MLP	One-hidden layer MLP model with 2 neurons, Levenberg-Marquardt backpropagation learning algorithm, and logarithmic sigmoid and linear transfer functions in the hidden and output layers, respectively	Average absolute deviation = 1.637%	Giwa et al. (2015)
MLP	One-hidden layer MLP model with 6 hidden neurons, Levenberg–Marquardt backpropagation learning algorithm, and hyperbolic tangent and linear transfer functions in the hidden and output layers, respectively	MSE = 0.0135	Rocabruno-Valdés et al. (2015)
MLP	Two-hidden layer MLP model with 7 and 5 neurons in the second and third hidden layers, respectively, and tangent sigmoid and linear transfer functions in the hidden and output layers, respectively	R^2 = 0.95 RMSE = 2.53	Miraboutalebi et al. (2016)
MLP - PLS	14 one-hidden layer MLP models with 21–30 neurons in the hidden layer as inner model of the partial least square (PLS) approach, Levenberg–Marquardt backpropagation learning algorithm, and tangent sigmoid and linear transfer functions in the hidden and output layers, respectively	R^2 = 0.9934 MSE = 0.723	Hosseinpour et al. (2016)

Table 4.7

Continued

Model used	**Characteristics**	**Statistical performance**	**Ref.**
ME#16	Input paramters were $\sum PUFAMs,\ \sum SFAMs]$	R^2 = 0.988 RMSE = 5.5945	Current study
RBFNN#5	Input paramters were $[\sum MUFAMs, \sum PUFAMs]$	R^2 = 0.7528 RMSE = 5.3128	
ME#22	Input paramters were $[\sum MUFAMs, \sum PUFAMs, \sum SFAMs]$	R^2 = 0.7294 RMSE = 5.4981	

CHAPTER V

Conclusion and Future Work

This chapter presents conclusions based on the research findings according to the objective of the research and gives recommendations accordingly

Conclusions

In this study, the effect of the effect the sum of the saturated, monounsaturated and polyunsaturated on the prediction CN was investigated. 36 models with various input combinations were developed. Furthermore, the proposed models were compared in terms of predictive accuracy to select the best model. The most important results can be summarized in the following cases:

- For case I (one input parameter), RBFNN#2 and ME#4 models gave the highest value of R^2 and lowest value of RMSE.
- For case II (two inputs parameters), that ME#16 with a combination of $[\sum PUFAMs, \sum SFAMs]$ has the highest value of R^2, while RBFNN#5 with combination of $[\sum MUFAMs, \sum PUFAMs]$ has the lowest value of RMSE with a value of 5.3128.
- For case III (three inputs parameters), ME#22 with a combination of $[\sum MUFAMs, \sum PUFAMs, \sum SFAMs]$ has shown good prediction accuracy with value of R^2 and RMSE of 0.7294 and 5.4981
- Two parameter combinations of input variables are satisfactory to estimate the CN with great accuracy.
- The results showed that $\sum PUFAMs$ has shown most significant effect on the value of CN
- The mathematical models and RBFNN have performed well and presented high accuracy in estimating the value of CN for the biodiesel samples

Future work

In the present study, the effect of storage period and condition on the value of CN was not taken into account. Thus, measuring CN of various type of biodiesel at different storage period and condition will be future research. Besides, the effect of fatty acid profile, storage period and storage condition on the prediction of CN value should be considered for future work. Moreover, the accuracy of developing a hybrid artificial neural should investigate to understand the influence of these parameters on CN value.

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Appendices

Appendix A

Cetane Number for Different Type of Biodiesel

Biodiesel name	$\sum MUFAMs$	$\sum PUFAMs$	$\sum SFAMs$	**CN**
Capric acid ester	0	0	100	47.2
Lauric acid ester	0	0	100	60.8
Myristic acid ester	0	0	100	66.2
Palmitic acid ester	0	0	100	74.3
Palmitoleic acid ester	100	0	0	51
Stearic acid ester	0	0	100	75.6
Oleic acid ester	100	0	0	56.5
Linoleic acid ester	0	100	0	38.2
Linolenic acid ester	0	100	0	22.7
Arachidic acid ester	0	0	100	100
Paullinic acid ester	100	0	0	64.8
Behenic acid ester	0	0	100	79.49
Erucic acid ester	100	0	0	76
Lignoceric acid ester	0	0	100	82.23
Anacardiaceae Rhus succedanea Linn	46.8	27.8	25.4	52.22
Annonaceae Annona reticulata Linn	52.6	21.7	25.7	53.47
Thevetia peruviana Merrill	60.9	12.6	26.5	57.48
Vallaris solanacea Kuntze	35.3	40.4	24.3	50.26
Balanitaceae Balanites roxburghii Planch	36.7	38.5	24.8	50.46
Burseraceae Canarium commune Linn	38.3	23	38.7	55.58
Terminalia chebula Retz	37.3	39.8	22.9	49.6
Compositaceae Vernonia cinerea Less	32	22	46	57.51
Croton tiglium Linn	56	29	15	49.9
Jatropa curcas Linn	40.8	32.1	27.1	52.31
Joannesia princeps Vell	45.8	46.4	7.8	45.2
Putranjiva roxburghii	33	3	118.99	
Sapium sebiferum Roxb Flacourtiaceae	27.4	0	72.6	30.72
Guttiferae Calophyllum apetalum Wild	48	30	22	51.57
Calophyllum inophyllum Linn	45.2	15.8	39	57.3
Garcinia combogia Desr	57.9	1.2	40.9	61.5
Garcinia indica Choisy	39.4	1.7	58.9	65.16
Garcinia echinocarpa Thw	52.6	0	47.4	63.1
Garcinia morella Desr	49.5	0.9	49.6	63.52
Mesua ferrea Linn	60	15	25	55.1

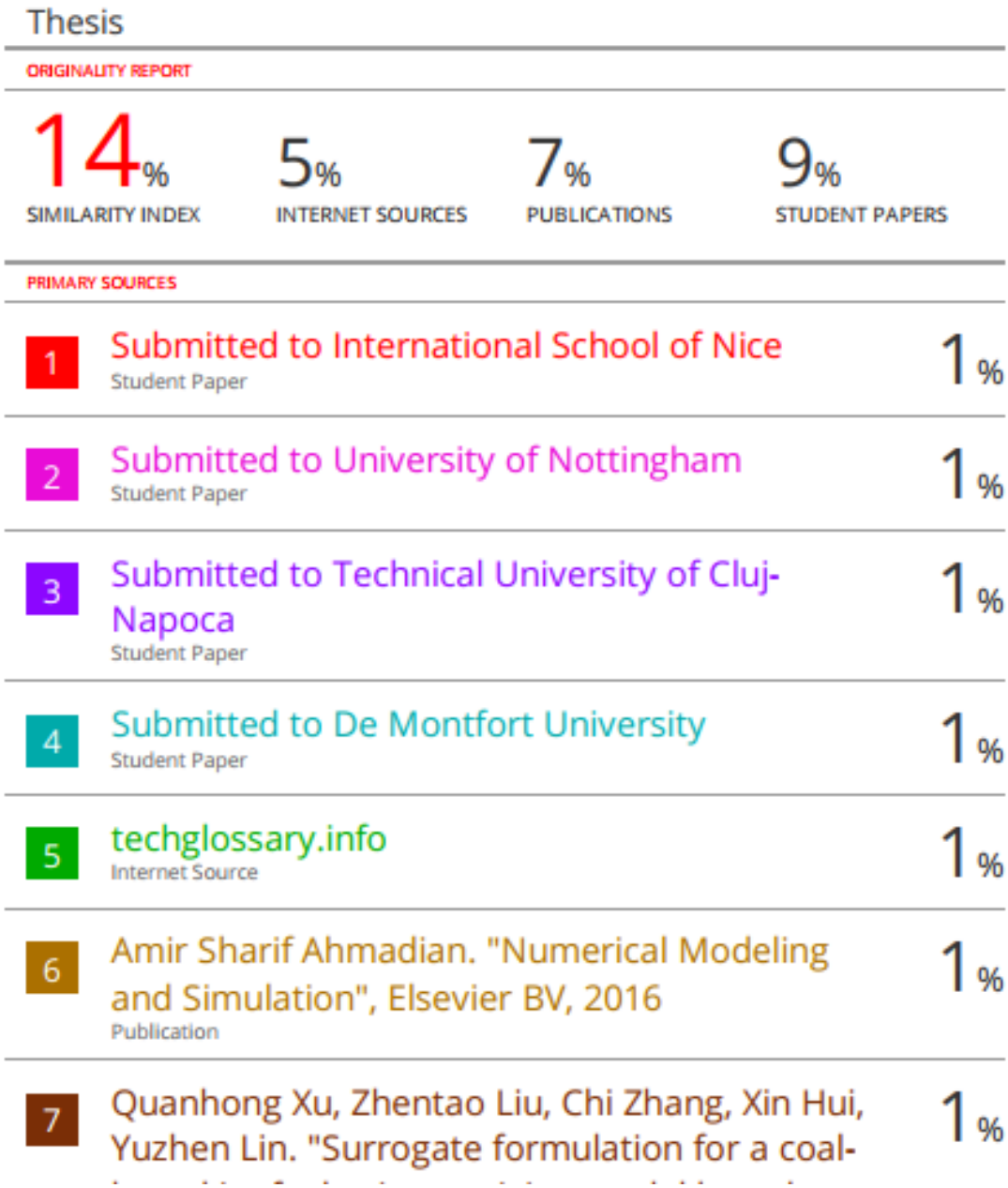
Icacinaceae Mappia foetida Milers	38.4	36.8	24.8	50.7
Illiciceae Illicium verum Hook	63.24	24.4	12.36	50.71
Labiatae Saturega hortensis Linn	12	80	8	25.46
Lauraceae Actinodaphne angustifolia	5.4	0	94.6	63.2
Neolitsea cassia Linn	4	3.3	92.7	64.05
Neolitsea umbrosa Gamble	21	6.7	72.3	60.77
Meliaceae Aphanamixis polystachya Park	21.5	42.6	35.9	48.52
Azadirachta indica	61.9	7.5	30.6	57.83
Melia azadirach Linn	22.3	67.7	9.4	41.37
Swietenia mahagoni Jacq	56	16.1	24.5	52.26
Menispermaceae Anamirta cocculus Wight & Hrn	46.4	0	53.6	64.26
Moraceae Broussonetia papyrifera Vent	14.8	72	13.1	41.25
Moringaceae Moringa concanensis Nimmo	83.8	0.8	15.4	56.32
Moringa oleifera Lam	81.5	0.9	17.6	56.66
Myristicaceae Myristica malabarica Lam	44.1	1	54.9	61.81
Papaveraceae Argemone mexicana	18.5	61.4	20.1	44.45
Papilionaceae Pongamia pinnata Pierre	51.8	19	29.2	55.84
Rhamnaceae Ziziphus mauritiana Lam	68.7	12.4	18.9	55.37
Rubiaceae Meyna laxiflora Robyns	32.5	39.7	27.8	50.42
Rutaceae Aegle marmelos correa Roxb	30.5	44.1	25.4	48.3
Salvadoraceae Salvadora oleoides Decne	8.3	0.1	91.6	66.13
Salvadora persica Linn	5.4	0	94.6	67.47
Sapindaceae Nephelium lappaceum Linn	49.5	0	50.5	64.86
Sapindus trifoliatus Linn	55.1	8.2	36.7	59.77
Sapotaceae Madhuca butyracea Mac	27.5	3	69.5	65.27
Madhuca indica JF Gmel	46.3	17.9	35.8	56.61
Mimusops hexendra Roxb	63	3	34	59.32
Urticaceae Urtica dioica Linn	14.6	76.4	9	38.73
Verbenaceae Tectona grandis Linn	29.5	46.8	23.7	48.31
Arachis hypoga Linn	40.07	40.69	19.39	48.86
Cocos nucifera	4.7	0.96	94.37	65.8
Oryza sativa	41.79	35.36	22.88	50.09
Elaeis guineensis	45.56	11.07	43.79	59.11
Glycine max (L.) merr	24.04	61.93	14.07	42.21
Helianthus annuus L.	22.52	67.12	10.39	41.41
Zea mays L.	35.3	48.58	16.15	46.3
Arachis hypogaea Linn.	63.57	16.46	20.21	54.03
Sesamum orientale L.	35.52	49.85	14.66	45.91
Sesamum indinum L.	41.21	44.61	14.2	46.92
Prunus dulcis	69.14	22.63	8.24	50.54
Brassica rapa (napus)	66.06	26.32	7.61	52.98

Carthamus tinctorius Linn.	14.19	76.72	9.12	39.32
Olea europoea Linn.	81.09	4.73	14.22	55
Irvingia malayana Oliv. ex A.W. Benn	3.07	0.44	96.21	66.13
Parinari anamensi Hance	43.52	19.59	36.89	56.35
Ceiba pentandra (L.) Gaertn.	26.51	43.76	29.64	49.52
Dipterocarpus alatus Roxb. ex G. Don	21.98	61.94	17	40.29
Ricinus communis L.	31.15	44.56	24.29	48.32
Jatropha currcas L.	41.79	38.88	19.34	48.91
Nicotiana tabacum L.	11.01	75.8	13.19	40.1
Citrus maxima (Burm.) Merr	24.7	45.32	30.02	49.29
Carica papaya Linn.	73.36	5.12	21.56	56.27
Nephelium lappaceum L.	56.21	3.98	39.6	61.17
Cucurbita moschata Duchesne	38.75	33.18	28.11	51.87
Citrus reticulate Blan co	21.38	52.45	26.03	46.48
Dasymaschalon lomentaceum Fiet & Gagnep	47	14.91	38.11	57.35
Rapeseed	64.1	30.5	5.4	46
Soybean	22.8	62.3	14.1	48
Rubber seed	27.8	51.1	21	51
Cottonseed	19.2	55.8	23.8	52.1
Jatropha	42.1	31.1	26.2	54
Karanja	53.2	19.1	17.8	52
Jatropha:palm 50:50	42.7	20.3	36.4	59
Neem	41.3	16.7	39.6	58.7
Sunflower	44	10.8	44.2	61.6
Palm	43.1	10.5	45.6	64
Mahua	36.4	16.1	46.2	61.4
SFCt 50:50	19.4	32.6	44.4	54.6
Beef Tallow	42.4	3.8	45.3	58.8
JCt 50:50	26.1	18.3	52.2	58
Coconut	8.2	2.7	81.5	60
Inedible tallow	41.9	6.7	45.6	61.7
Canola	60.3	28.5	7.8	55
Lard	41.9	13.7	40.9	63.6
Yellow grease	48.8	15.8	27.9	52.9
Linseed	20	73	7	52
Wild mustard	59.1	27.2	3.6	61.1
Waste palm oil	44.1	10.7	44.3	60.4
Palm	46.4	8.9	44.7	61
Olive	76	8.4	15.6	57
Peanut	55.7	28.7	15.6	53
Rape	65.3	28.3	6.5	55

Soybean	25.6	59.1	15.3	49
Sunflower	25.6	63.3	11.1	50
Grape	19.1	69.4	11.3	48
H.O. Sunflower	62.9	27.6	9.3	53
Corn	66.4	25.3	8.1	53
Almond	77.6	8.4	13.9	57
Apocynaceae Ervatamia coronaria Stapf	50.9	16.4	32.5	56.33
Cannabinaceae Cannabis sativa Linn	15	80	0	36.4
Combretaceae Terminalia bellirica Roxb	24	31	35	56.24
Corylaceae Corylus avellana	88	2.9	8.9	54.5
Aleurites moluccana Wild	10.5	77	12.2	34.18
Euphorbia helioscopia Linn	18.8	64.8	19.3	34.25
Perilla frutescens Britton	9.8	83.7	0	30.09
Litsea glutinosa Robins	2.3	0	96.3	64.79
Magnoliaceae Michelia champaca Linn	29.2	42.5	25.8	50.28
Rosaceae Princepia utilis Royle	32.6	43.6	22.4	48.94
Simaroubaceae Quassia indica Nooleboom	36	48	9	46.74
Sterculaceae Pterygota alata Rbr	44	32.4	23	51.09
Ulmaceae Holoptelia integrifolia	55.2	0	44.2	61.22

Appendix X

Turnitin Similarity Report



Thesis

ORIGINALITY REPORT

14%	5%	7%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to International School of Nice Student Paper	1%
2	Submitted to University of Nottingham Student Paper	1%
3	Submitted to Technical University of Cluj-Napoca Student Paper	1%
4	Submitted to De Montfort University Student Paper	1%
5	techglossary.info Internet Source	1%
6	Amir Sharif Ahmadian. "Numerical Modeling and Simulation", Elsevier BV, 2016 Publication	1%
7	Quanhong Xu, Zhentao Liu, Chi Zhang, Xin Hui, Yuzhen Lin. "Surrogate formulation for a coal-	1%