

**PREDICTIVE MODELLING FOR NITROGEN
OXIDES EMISSIONS OF DIESEL ENGINES
OPERATED WITH ALTERNATIVE PLASTIC FUEL**

MOHAMMAD NOR KHASBI BIN JARKONI

**DOCTOR OF PHILOSOPHY
UNIVERSITI MALAYSIA TERENGGANU**

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MOHAMMAD NOR KHASBI BIN JARKONI

**Thesis Submitted in Fulfilment of the Requirement for the Doctor of
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DEDICATION

Dedicated this thesis to:

My all: Abah & Mak

My siblings

My anchor throughout the storm & turbulence

I owe you guys, big time

Thanks a lot

May Allah bless

Abstract of thesis presented to the Senate of Universiti Malaysia Terengganu in fulfillment of the requirements for the degree of Doctor of Philosophy

PREDICTIVE MODELLING FOR NITROGEN OXIDES EMISSION OF DIESEL ENGINES OPERATED WITH ALTERNATIVE PLASTIC FUEL

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August 2024

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Faculty : Faculty of Ocean Engineering Technology

The rapid growth of plastic manufacturing has supported industrial development, but simultaneously intensified post-consumer plastic waste generation, raising serious environmental concerns. Pyrolysis, a thermal decomposition process in an oxygen-free environment, offers a promising pathway to convert plastic waste into diesel-like fuel. This study investigates commercial B10 (10% palm methyl ester) and two plastic-derived blends: HDPE10 (10% high-density polyethylene) and PP10 (10% polypropylene), and B0 (pure diesel) as guideline tested on a Yanmar L48N6-MTMRYI diesel engine following ISO 8178 D2. The objective is to characterize fuel properties, investigate the performance and emissions trend, and predict nitrogen oxides (NO_x) emissions using machine learning (ML) techniques. HDPE10 and PP10 were found to comply with commercial fuel standards, delivering improved brake power (BP), reduced brake-specific fuel consumption (BSFC), and enhanced brake thermal efficiency (BTE) compared to B0. However, emissions analysis revealed increased carbon monoxide (CO) and carbon dioxide (CO₂) across all blends: B10 (38% CO, 50% CO₂), HDPE10 (30% CO, 15% CO₂), and PP10 (45% CO, 41% CO₂).

Hydrocarbon (HC) emissions rose in HDPE10 (31%) and PP10 (21%) but declined significantly in B10 (48%). NO_x emissions decreased for all blends, with reductions of 23% in B10, 16% in HDPE10, and 14% in PP10. For NO_x prediction, the dataset was partitioned into 70% for training and 30% for testing using three ML algorithms: Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). All models demonstrated high predictive accuracy, with a Coefficient of Determination (R^2) exceeding 0.994. Among them, BR delivered the best performance, achieving R^2 between 0.99409–0.99992 and root mean square error (RMSE) between 0.003036–0.016761 g/kWh during training. Validation confirmed BR's reliability with R^2 of 0.988473–0.990847, RMSE of $8.7e^{-5}$ –0.0024 g/kWh, and normal absolute error (NAE) of $1.35e^{-7}$ – $1.42e^{-5}$. These findings confirm the feasibility of HDPE10 and PP10 as viable diesel alternatives and highlight the effectiveness of ML, particularly the BR algorithm, in supporting NO_x emissions prediction for cleaner fuel development in Malaysia.

Abstrak tesis yang dikemukakan kepada Senat Universiti Malaysia Terengganu sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah

**PERMODELAN RAMALAN UNTUK PELEPASAN OKSIDA NITROGEN
OLEH ENJIN DIESEL YANG DIKENDALIKAN DENGAN BAHAN API
PLASTIK ALTERNATIF**

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Pertumbuhan pesat dalam industri pembuatan plastik menyokong pembangunan industri secara menyeluruh, namun turut meningkatkan penjejanaan sisa plastik pasca guna ketara, sekali gus menimbulkan kebimbangan serius terhadap kelestarian alam sekitar. Pirolisis, iaitu proses penguraian haba tanpa kehadiran oksigen, menawarkan pendekatan berpotensi menukarkan sisa plastik kepada bahan api seakan diesel. Kajian ini menyiasat prestasi campuran B10 komersial (10% metil ester sawit) dan dua campuran bahan api berasaskan plastik; HDPE10 (10% polietilena berketumpatan tinggi) dan PP10 (10% polipropilena), dan B0 (diesel tulen) sebagai penanda aras diuji menggunakan enjin diesel Yanmar L48N6-MTMRYI mengikut piawaian ISO 8178 D2. Objektif utama kajian adalah mencirikan sifat bahan api, menilai tren prestasi dan pelepasan, serta meramal pelepasan nitrogen oksida (NO_x) menggunakan teknik pembelajaran mesin (ML). Hasil menunjukkan HDPE10 dan PP10 memenuhi piawaian bahan api komersial, dengan peningkatan dalam kuasa brek (BP), pengurangan penggunaan bahan api spesifik brek (BSFC), serta peningkatan kecekapan terma brek (BTE) berbanding B0. Namun, analisis pelepasan menunjukkan

peningkatan karbon monoksida (CO) dan karbon dioksida (CO₂) bagi semua campuran: B10 (38% CO, 50% CO₂), HDPE10 (30% CO, 15% CO₂), dan PP10 (45% CO, 41% CO₂). Pelepasan hidrokarbon (HC) meningkat dalam HDPE10 (31%) dan PP10 (21%), manakala B10 menunjukkan pengurangan ketara sebanyak 48%. Pelepasan NO_x menurun bagi kesemua campuran; B10 mencatatkan pengurangan tertinggi sebanyak 23%, diikuti HDPE10 (16%) dan PP10 (14%). Bagi tujuan ramalan NO_x, set data telah dibahagikan kepada 70% untuk latihan dan 30% untuk pengujian menggunakan tiga algoritma ML: Levenberg-Marquardt (LM), Bayesian Regularization (BR), dan Scaled Conjugate Gradient (SCG). Ketiga-tiga model menunjukkan ketepatan ramalan tinggi dengan nilai pekali penentuan (R²) melebihi 0.994. Algoritma BR mencatatkan prestasi terbaik dengan R² antara 0.99409–0.99992 dan ralat purata kuasa dua (RMSE) antara 0.003036–0.016761 g/kWh semasa latihan. Pengesahan model turut mengukuhkan kebolehpercayaan BR dengan R² antara 0.988473–0.990847, RMSE antara 8.7e⁻⁵–0.0024 g/kWh, dan ralat mutlak normal (NAE) antara 1.35e⁻⁷–1.42e⁻⁵. Dapatan kajian ini mengesahkan kebolegunaan HDPE10 dan PP10 sebagai bahan api alternatif yang berdaya saing serta menunjukkan keberkesanan kaedah ML, khususnya algoritma BR, dalam meramal pelepasan NO_x bagi menyokong pembangunan bahan api diesel yang lebih bersih di Malaysia.

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APPROVALS

I certify that an Examination Committee has met on 15th August 2024 to conduct the final examination of Full Name, on his Doctor of Philosophy thesis entitled **“Predictive Modelling for Nitrogen Oxides Emission of Diesel Engines Operated with Alternative Plastic Fuel”** in accordance with the regulations approved by the Senate of Universiti Malaysia Terengganu. The Committee recommends that the candidate be awarded the relevant degree. The members of the Examination Committee are as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UMT or other institutions.

MOHAMMAD NOR KHASBI BIN JARKONI

Date:

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LIST OF ABBREVIATIONS

AF	Air-fuel
ANN	Artificial Neural Network
ATR	Attenuated total reflectance
BP	Brake power
BR	Bayesian Regularization
BSFC	Brake-specific fuel consumption
BTE	Brake thermal efficiency
B0	Pure/conventional diesel
B7	7% palm methyl ester and 90% regular diesel fuel
B10	10% palm methyl ester and 90% regular diesel fuel
B20	20% palm methyl ester and 80% regular diesel fuel
B50	50% palm methyl ester and 50% regular diesel fuel
B100	100% palm methyl ester and
BPA	Bisphenol A
CARB	California Air Resources Board
CO	Carbon monoxide
CO ₂	Carbon dioxide
CHNS	Carbon, Hydrogen, Nitrogen, and Sulphur
COPD	Chronic obstructive pulmonary disease
CPO	Crude palm oil
DALYs	Disability-adjusted life years
DEA	Diesel engine application
FAME	Fatty acid methyl esters
FFAs	Free fatty acids
FID	Flame ionization detector
FTIR	Fourier transform infrared
GDP	Gross domestic product
GHG	Greenhouse gases
GC-FID	Gas chromatograph with flame ionization detection
HC	Hydrocarbon
HCN	Hydrogen cyanide

HDPE	High-density polyethylene
HDPE10	10% HDPE and 90% regular diesel fuel
H ₂ O	Water
IoT	Internet of Things
IQR	Interquartile range
ITF	International Transport Forum
KOH	Potassium hydroxide
LDPE	Low-density polyethylene
LM	Levenberg-Marquardt
MATLAB	Matrix Laboratory
MIDA	Malaysia Investment Development Authority
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean square error
MSW	Municipal solid waste
MTOE	Metric tons of oil equivalent
MWh	Megawatt-hours
NaOH	Sodium hydroxide
NAE	Normal absolute error
NEA	National Environment Agency
NMOG	Non-methane organic gases
NO	Nitric oxide
NO _x	Nitrogen oxide
NO ₂	Nitrogen dioxide
O	Oxygen element
OH	Hydroxyl
O ₂	Oxygen
PBDE	Polybrominated diphenyl ether
PET/PETE	Polyethylene terephthalate
PI	Performance indicator
PM	Particulate matter
ppm	Part per million
PP	Polypropylene
PP10	10% PP and 90% regular diesel fuel
PS	Polystyrene

PVC	Polyvinylchloride
R	Determination of correlation
RMSE	Root mean square error
R^2	Determination of determination
SCG	Scale Conjugate Gradient
SO ₂	Sulphur dioxide
SO _x	Sulphur oxides
THC	Total hydrocarbons
TWh	Terawatt-hours
US EPA	United States Environmental Protection Agency
VOC	Volatile organic compound
WHO	World Health Organization

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Technological advancements have changed many industries, including transportation, construction, and manufacturing. Innovations like self-driving vehicles, 3D printing, and Industry 4.0, marked by automation, artificial intelligence (AI), and the Internet of Things (IoT), have transformed how people live and work. These innovations have made processes more efficient, driven economic growth, opened new opportunities, changed how businesses operate, and how people use technology. In the transportation sector, diesel engine applications (DEA) are central to these changes. Diesel engines are known for their durability, efficiency, and versatility, powering everything from heavy-duty trucks on highways to ships that transport goods across oceans. They are essential for moving important goods, keeping supply chains running, and connecting people and businesses worldwide (Cames & Helmers, 2013; Kartsan *et al.*, 2024; Lane, 2019). This makes DEA not just a technological achievement, but also a vital part of modern life. Beyond their industrial use, diesel engines also affect daily life by enabling efficient travel. They help people commute to work, go to school, and carry out everyday activities reliably. DEA forms the infrastructure backbone that supports the global economy, allowing businesses to expand, reach new markets, and compete in an interconnected world (Calero *et al.*, 2023; Castro Verdezoto *et al.*, 2019; Paykani *et al.*, 2022). The significance of the DEA extends beyond its immediate utility. Its role in supporting large-scale production, transportation, and commerce directly contributes to economic growth, creates trade opportunities, and stimulates activity in other sectors. As industries and societies evolve, the dependence on current technologies grows. Therefore, the ongoing development of diesel engine technologies

is essential to ensure they remain efficient, reliable, and environmentally sustainable in the face of challenges like climate change and rising energy demands.

While technological advancements in the transportation sector have made travel faster and more efficient, they have also come with significant environmental and societal challenges. As much as the DEA has revolutionized the way goods and people move, it also contributes to air pollution, greenhouse gas (GHG) emissions, traffic congestion, and other issues that have far-reaching impacts on the planet and health (US EPA, 2024; Manisalidis *et al.*, 2020). Air pollution is one of the most concerning consequences of diesel engine use. The World Health Organization (WHO) highlights that transportation-related air pollution leads to approximately 7 million premature deaths globally each year, affecting respiratory and cardiovascular health (WHO, 2024a). Diesel engines are also major contributors to GHG emissions, which accelerate climate change. According to the International Transport Forum (ITF), the transportation sector is responsible for 24% of global carbon dioxide (CO₂) production, a figure projected to rise by 16% by 2050 (ITF, 2021). Moreover, the growth of transportation networks, improving connectivity, has also led to significant traffic congestion, especially in urban areas. The time lost in traffic not only causes frustration but also has a tangible economic cost. In the United States alone, traffic congestion results in an estimated \$88 billion in wasted time and fuel each year (Afrin & Yodo, 2020; Funk & Volz, 2022). These issues: air pollution, emissions, and congestion, are a direct consequence of the widespread adoption of diesel engine technology and highlight the need for more sustainable solutions. As the continuity relies on the DEA for economic growth and mobility, it becomes increasingly clear that one must find ways to mitigate their environmental and societal impacts. This is where research into more sustainable engine technologies and predictive modelling, such as the forecasting of nitrogen oxides (NO_x) emissions, becomes essential (Meng *et al.*, 2025; Pillai *et al.*, 2022).

NO_x emissions from diesel engines are a significant source of air pollution, with far-reaching effects on both human health and the environment. NO_x, primarily composed of nitrogen dioxide (NO₂) and nitric oxide (NO), is released during the combustion process in diesel engines and contributes to the formation of ground-level

ozone and fine particulate matter (PM_{2.5} and PM₁₀). These pollutants are harmful to human health, especially for those with respiratory conditions like asthma, chronic obstructive pulmonary disease (COPD), and bronchitis (Dowlatabadi *et al.*, 2024; Jo *et al.*, 2017; Kim *et al.*, 2013). Studies show that NO_x exposure can worsen lung function, lead to chronic respiratory problems, and increase the incidence of cardiovascular diseases. The WHO attributes approximately 4.2 million premature deaths annually to outdoor air pollution, with a significant proportion of these deaths linked to NO_x emissions from transportation (WHO, 2024). Beyond their direct impact on human health, NO_x emissions also contribute to environmental degradation. When NO_x reacts with volatile organic compounds (VOC) in the presence of sunlight, it forms ground-level ozone, which is a major component of smog. Ground-level ozone can damage crops, forests, and other ecosystems, impairing biodiversity and agricultural productivity. NO_x also contributes to acid rain, which can harm soil and water bodies, disrupt ecosystems, and lead to the acidification of lakes and rivers (US EPA, 2024; Kalender & Alkan, 2019). According to the U.S. Environmental Protection Agency, transportation accounts for approximately 40% of total NO_x emissions in the United States, with diesel-powered vehicles being one of the largest contributors (US EPA, 2024b). Globally, the transportation sector is responsible for a substantial share of NO_x emissions, with the ITF projecting that emissions from transportation will rise by 16% by 2050 unless significant reductions are made through stricter emission standards and the adoption of cleaner technologies (ITF, 2021).

The DEA has brought advancements to transportation, but it also contributes to significant environmental challenges concerning wildlife and natural habitats. The construction of transportation infrastructure, including roads, highways, and railways, often leads to habitat destruction and fragmentation, disrupting ecosystems and hindering wildlife movement. Such fragmentation reduces the connectivity between critical habitats that many species rely on for migration, foraging, and breeding. When animals are cut off from these vital areas, it not only affects their ability to survive but can also lead to diminished genetic diversity, which increases the risk of species decline. Research by Broekman *et al.* (2024) and Barrientos *et al.* (2021) revealed that transportation infrastructure has reduced habitat connectivity for mammals globally by as much as 30%. Large animals like elephants and tigers, which depend on extensive

territories, face difficulties in navigating fragmented landscapes. This isolation not only makes it harder for them to find resources but also raises the likelihood of vehicle collisions and disrupts their breeding patterns. Additionally, emissions from diesel engines, such as NO_x and particulate matter (PM), pose further risks to wildlife. These pollutants can accumulate on vegetation, harming plants that herbivores depend on for food (Guerrieri *et al.*, 2024). They also make their way into water systems where they degrade aquatic environments, affecting fish and other species that rely on clean water for survival. The knock-on effects from these pollutants can ripple through entire ecosystems, disrupting food chains and leading to long-term ecological harm (Gokul *et al.*, 2023; Manisalidis *et al.*, 2020).

Noise pollution from diesel engines is another issue that disrupts wildlife. Many species, including marine mammals like whales and dolphins, rely on sound for communication and navigation. Excessive noise from vehicle engines or ships can interfere with these critical behaviours, leading to disorientation, stress, and sometimes even death (Dähne *et al.*, 2019; Marley *et al.*, 2019; Schoeman *et al.*, 2020). Similarly, on land, noise from traffic disturbs the daily routines of birds, amphibians, and other animals, affecting their ability to breed and forage effectively (Erbe *et al.*, 2022; Kok *et al.*, 2023). Chronic exposure to excessive noise, especially from sources like traffic, industrial activities, and urban environments, can have a profound impact on both physical and mental health. To human life, one of the most significant consequences of noise pollution is its link to cardiovascular diseases. Prolonged exposure to high levels of noise, particularly from traffic, has been shown to increase the risk of conditions such as hypertension, heart attacks, and strokes. WHO estimates that noise pollution causes around 1 million disability-adjusted life years (DALYs) in Europe alone, with cardiovascular diseases accounting for most of this burden (WHO, 2018). This is largely due to how noise triggers the body's stress response, elevating cortisol levels (the stress hormone), as well as heart rate and blood pressure can damage the cardiovascular system. Beyond the physical effects, noise pollution also takes a toll on mental well-being. Ongoing exposure to noise has been linked to increased stress, anxiety, and depression. Those living in noisy urban areas often struggle with sleep disturbances, which can worsen mental health issues (Münzel *et al.*, 2020). Several studies have found that individuals in high-noise environments, particularly from

traffic, have a greater likelihood of developing anxiety disorders and depression. Sleep disruption plays a key role here, as noise interrupts restorative sleep cycles, leading to fatigue and reduced cognitive function (Hahad *et al.*, 2024; Nobile *et al.*, 2023).

The transport sector plays a critical role in driving Malaysia's economic development, enabling the movement of goods, services, and people, which supports industries such as manufacturing, retail, and tourism. As the largest energy consumer in the country, the transport sector accounted for 38.5% (24,039 kt) of the total energy consumption in 2017 (Solaymani, 2022). This high energy demand is largely due to the sector's heavy reliance on petroleum-based fuels, particularly diesel and gasoline. These fuels have been crucial in fostering economic growth and improving mobility, but their widespread use has also led to significant environmental challenges. Globally, the transport sector remains the largest consumer of energy, accounting for nearly one-third of the world's total energy use. Road transport alone is responsible for a substantial portion of this consumption (Lindstad *et al.*, 2023; Ntuli *et al.*, 2024). Petroleum continues to be the dominant source of energy worldwide, with nearly half of global petroleum consumption attributed to the transportation sector. Despite the growing focus on sustainable energy sources, energy density, availability, and established infrastructure in the petroleum sector have made it the fuel of choice for most transportation systems. However, this continued reliance on petroleum poses significant environmental and health risks (Dowlatabadi *et al.*, 2024; Morón *et al.*, 2021; Nobile *et al.*, 2023). As the global population continues to grow, it is projected to reach between 9.4 billion and 12.7 billion by the end of the century. The demand for energy, especially for transportation, will also increase intensely (Gerland *et al.*, 2014; Gu *et al.*, 2021). This growth, coupled with urbanization and rising mobility, will place even more pressure on the transport sector to meet energy demands while addressing the environmental and health challenges linked to traditional and conventional fuel consumption. As a result, finding sustainable alternatives to petroleum-based fuels has become an urgent priority, both to meet energy needs and reduce the harmful effects of transportation on the planet and public health.

The growing demand for energy to fuel the rapidly expanding global economy and key industries has resulted in the excessive release of harmful exhaust pollutants

and GHGs into the environment. The transportation sector, which is essential for the movement of goods and people, is a major contributor to this issue. Common pollutants from vehicle emissions include carbon monoxide (CO), NO_x, unburned hydrocarbons (HC), and PM alongside GHG such as CO₂, which significantly impact climate change and global warming (Kumari *et al.*, 2021; Mohammed *et al.*, 2023; Yusri *et al.*, 2019). Among the various modes of transportation, road transport is one of the largest sources of local air pollution. The high number of vehicles on the road, particularly in densely populated urban areas, leads to the release of significant amounts of NO_x and PM. These pollutants contribute to poor air quality, leading to the formation of ground-level ozone and fine particulate matter, both of which pose severe health risks (Paykani *et al.*, 2022; Solaymani, 2022; Yusoff *et al.*, 2021). The ITF reports that road transport accounts for around 14% of global NO_x emissions, making it a significant contributor to air pollution, particularly in cities with heavy traffic (ITF, 2021). On a global scale, marine transport also plays a crucial role in air pollution, although its impact is more widespread. Ships, particularly those that use heavy fuel oil, emit large amounts of sulphur oxides (SO_x) and NO_x. These emissions contribute not only to air pollution but also to the formation of acid rain and the degradation of marine ecosystems. Marine transport accounts for approximately 15% of global NO_x emissions, with a considerable environmental impact on regions with high shipping activity such as Southeast Asia and the Mediterranean (Mueller *et al.*, 2023; Sadeghinezhad *et al.*, 2013). These pollutants, whether from road or marine transport, have a direct and harmful effect on human health. Once released into the atmosphere, substances like NO_x and PM can be inhaled, entering the respiratory system where they can be deposited in tissues and organs. Over time, exposure to these toxic gases contributes to a range of health problems, particularly respiratory and cardiovascular diseases. WHO estimates that air pollution causes approximately 7 million premature deaths each year, with many of these deaths linked to diseases such as bronchitis, asthma, lung cancer, and heart disease (Mohd Noor *et al.*, 2018; Sadeghinezhad *et al.*, 2013).

The elderly, children, women, and individuals with pre-existing respiratory conditions are particularly vulnerable to the harmful effects of air pollution. These groups are more susceptible to respiratory and cardiovascular diseases caused by

pollutants (Alawa and Chakma, 2023; Hänggi *et al.*, 2019; Striebig *et al.*, 2019). For example, developing lungs in children are more sensitive to air pollutants, which can lead to chronic conditions like asthma. Similarly, the elderly often experience aggravated heart and lung diseases when exposed to high levels of pollution. As air pollution continues to increase globally, these vulnerable groups face growing health risks, underscoring the urgent need for measures to mitigate its effects (Roche *et al.*, 2024). The rapid increase in global energy demand driven by industrialization and population growth has raised significant concerns about sustainability and environmental degradation. The transportation and industrial sectors release pollutants that not only harm human health but also have far-reaching environmental consequences. Pollution from vehicles and industrial activities does not stay confined to urban centres; it can travel across long distances carried by winds and sea breezes, affecting even remote areas (Aydın, 2020; Striebig *et al.*, 2019). This issue is particularly evident in rapidly developing countries like China, where the past few decades have seen massive economic growth. From 1981 to 2009, the gross domestic product (GDP) of China grew by 66.02%, and industrial waste increased by over five times, reaching 2.04 billion tons (Bian *et al.*, 2015).

By 2007, China had become the world's largest consumer of energy and the largest emitter of CO₂, surpassing the United States (Wang *et al.*, 2013). While boosting the economy, this growth has also resulted in significant environmental challenges, as fossil fuel consumption, especially coal, continues to contribute to global pollution and climate change. As the global population is projected to grow and energy demands increase, the pressure on the environment and public health intensifies unless meaningful actions are taken to transition to cleaner energy sources. Achieving this delicate balance requires a comprehensive approach that considers the environmental, economic, and social dimensions of energy use (Adekoya *et al.*, 2021; Wang *et al.*, 2021). As depicted in Figure 1.1, global energy consumption has steadily increased over the years. In 2018, global energy demand rose by 2.9%, nearly double the 10-year average growth rate of 1.5% per year. Since 2003, the world's total energy consumption has grown significantly, surpassing 10,000 million metric tons of oil equivalent (MTOE). The increase has been driven primarily by natural gas, which saw a more than 40% rise in consumption. While all forms of fuel experienced growth,

renewable energy, though expanding rapidly accounted for the second-largest increase in overall energy consumption (BP, 2019).

Figures 1.2 and 1.3 illustrate the trends in fossil fuel production and consumption in Malaysia, highlighting the dependence on coal, natural gas, and oil as primary energy sources. Coal production in Malaysia began in 1986 at a very modest rate, under 0.01 megawatt-hours (MWh) per person per year (Ritchie & Rosado, 2017). Over the years, fossil fuel production has steadily increased, reaching its peak in 2005 at 41.94 MWh. After this peak, production slightly declined but remained relatively stable until 2014, when the global energy landscape was largely shaped by natural gas, crude oil, and coal, which produced 689.71 terawatt-hours (TWh), 411.08 TWh, and 18.41 TWh, respectively. This rise in fossil fuel production closely mirrors the growing energy demand not only in Malaysia but globally, as countries continue to industrialize and urbanize. Energy consumption in Malaysia has followed a similar trend to oil, natural gas, and coal, accounting for a substantial share of the energy mix. Between 1965 and 2018, fossil fuel consumption surged, with oil making up 39.47% of total energy consumption, natural gas 38%, and coal 22.63%. This increasing reliance on non-renewable energy sources has fuelled economic growth, but it also presents several environmental and sustainability challenges. As Malaysia continues to develop, the challenge lies in balancing energy demand with environmental sustainability. The dependence on fossil fuels has undeniably supported its rapid growth, but it also highlights the urgent need to transition toward cleaner, renewable energy sources. This transition is crucial not only to protect public health and mitigate climate change but also to ensure that future generations inherit an energy system that is sustainable and capable of supporting long-term prosperity.

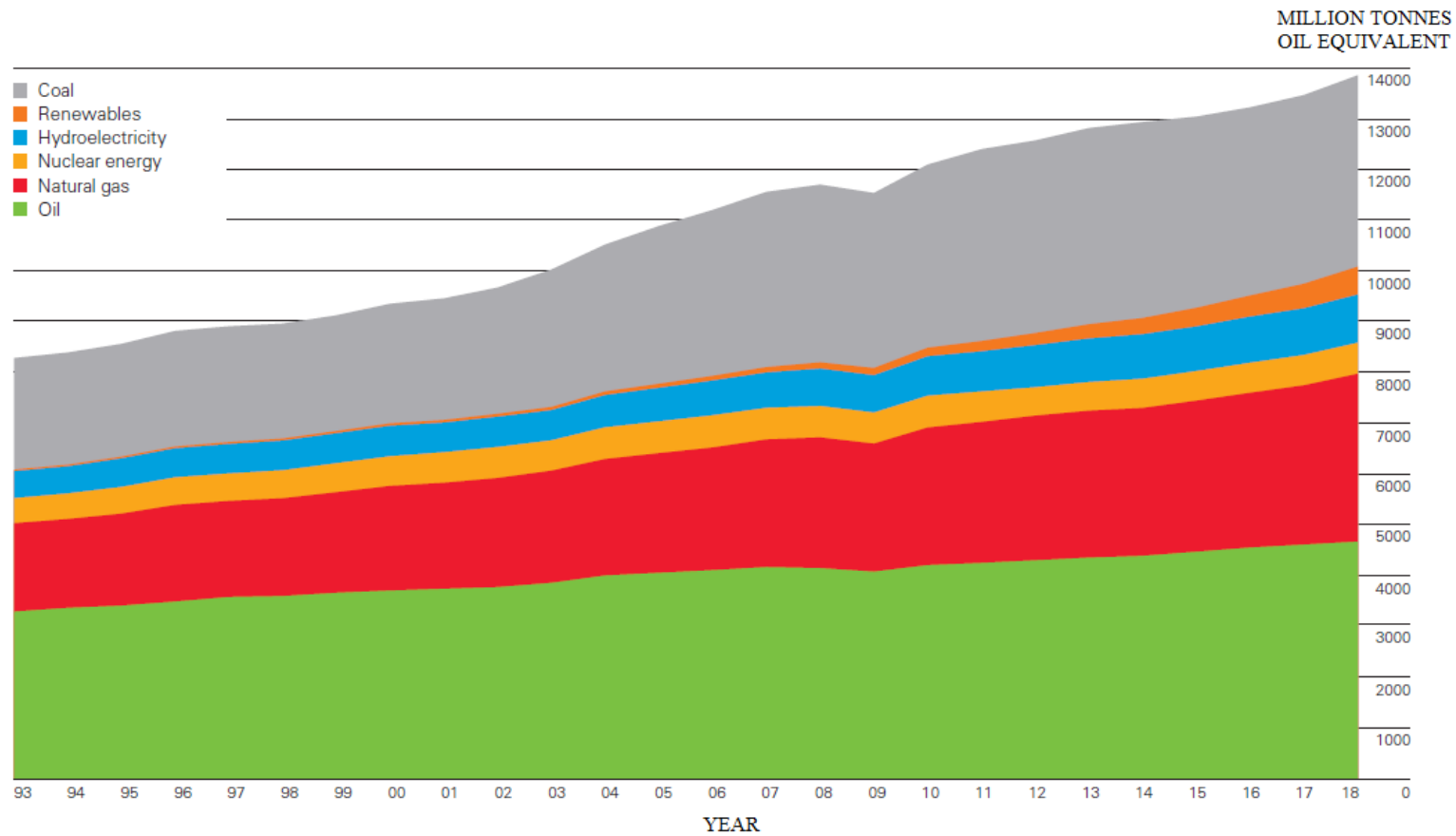


Figure 1.1 Total world energy consumption in MTOE (1993-2018) (Ritchie & Rosado, 2017)

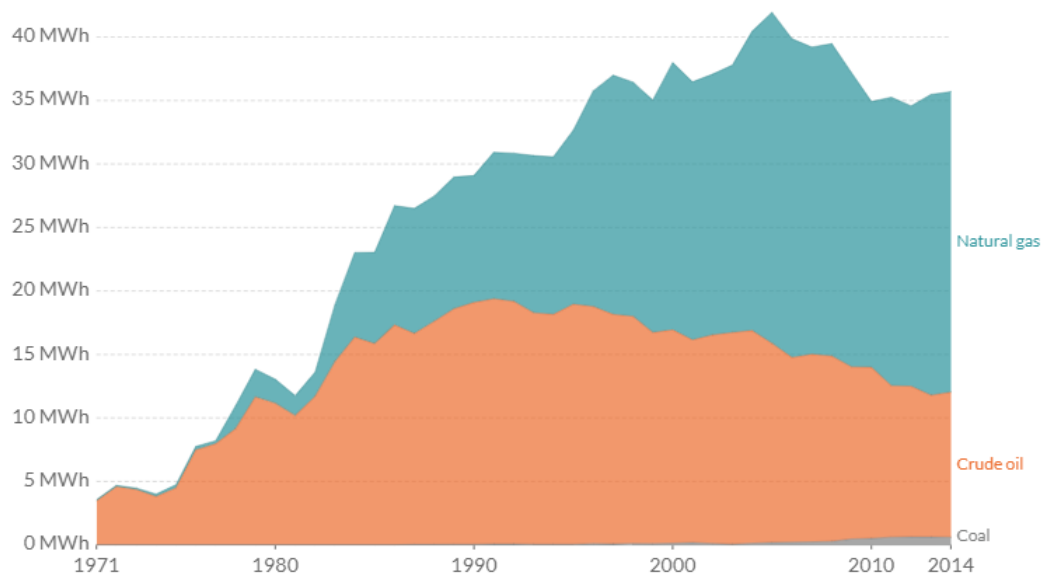


Figure 1.2 Total production of fossil fuels in Malaysia (Ritchie & Rosado, 2017)

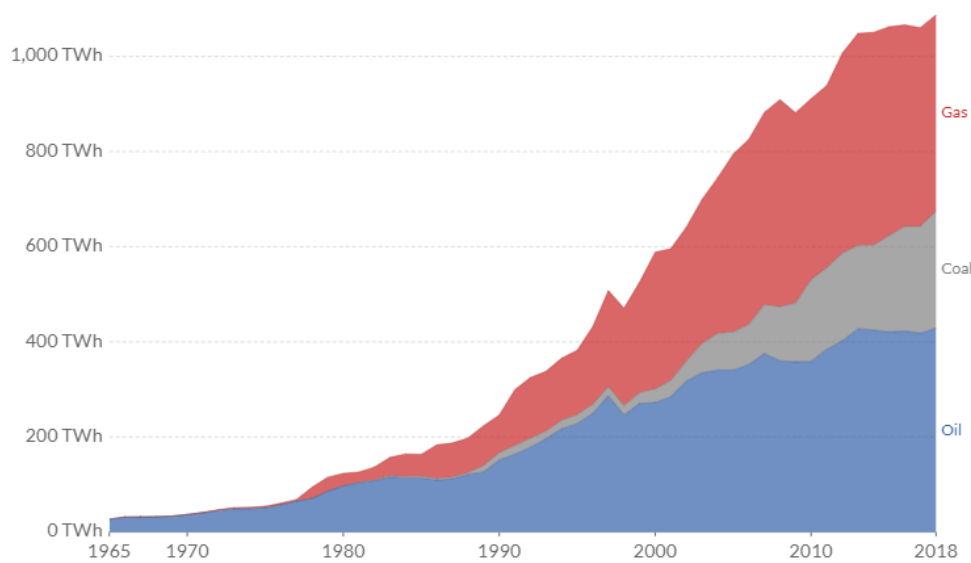


Figure 1.3 Fossil fuel consumption in Malaysia (Ritchie & Rosado, 2017)

One of the most promising solutions lies in addressing both energy consumption and the growing plastic waste crisis. Plastics were produced in massive quantities for their durability and versatility have become a major environmental concern due to their slow decomposition and widespread pollution. In recent years, converting plastic waste into diesel fuel through the pyrolysis process has emerged as an innovative and environmentally friendly solution (Blazsó, 2006; Qureshi *et al.*, 2020). Pyrolysis, which involves breaking down plastics at high temperatures in the absence of oxygen, not only provides a method for recycling plastic waste but also generates valuable fuel. This approach offers a green alternative for managing plastic waste while simultaneously producing energy, making it a promising technology for reducing the harmful environmental impacts of plastic pollution and fossil fuel reliance (Erdogan & Erdogan, 2020; Jeswani *et al.*, 2021; Qureshi *et al.*, 2020). Global plastic production has surged over the past several decades, driven by its widespread use in packaging, construction, automotive, and other industries (Baechler *et al.*, 2023; Maddison *et al.*, 2023; Shen *et al.*, 2020). According to Williams and Rangel-Buitrago (2022) and Alimba and Faggio (2019), plastic production has increased from 1.5 million metric tons in the 1950s to over 300 million metric tons annually by the 2020s. As plastic waste continues to accumulate in landfills and oceans, technologies like pyrolysis provide a way to recover valuable energy while addressing the plastic pollution crisis. By transforming plastic waste into usable fuel, pyrolysis offers a dual solution to the challenges of waste management and sustainable energy production, with the potential to reduce the environmental impact of both. However, further research and optimization are needed to enhance the efficiency and scalability of this technology. This ongoing research into sustainable waste management and energy recovery solutions highlights the importance of balancing environmental protection and public health.

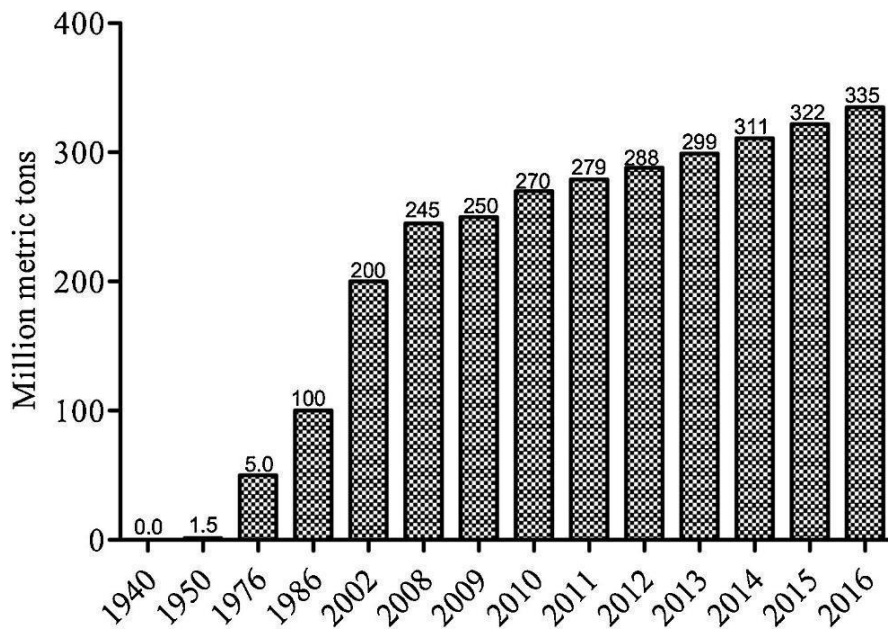


Figure 1.4 Increasing number of plastic manufacturing operations worldwide from 1950 to 2016 (Alimba & Faggio, 2019)

Research by Ncube *et al.* (2021) and Geyer *et al.* (2017) revealed that approximately 80% of plastic waste has ended up in landfills or scattered throughout the environment, totalling more than 6,300 million tons. The very qualities that make plastics so practical, such as their long-lasting durability and resistance to degradation, are also the reason they pose a persistent environmental challenge. Plastics, once discarded, do not break down easily and can remain in the environment for hundreds of years. Currently, the world generates around 300 million tons of plastic waste each year, contributing significantly to global pollution. Qureshi *et al.* (2020) highlight the widespread environmental impact, noting that a large portion of this plastic waste ends up in the oceans, where it poses a grave threat to marine life. Hidayah and Syafrudin (2018) estimated that between 4 and 12 million tons of plastic waste are dumped into the oceans annually, affecting marine animals that often ingest or become entangled in plastic debris. The disruption of marine ecosystems and food chains is profound as plastic pollution harms biodiversity and interferes with the health of aquatic life. Over time, plastics break down into smaller particles known as microplastics, further exacerbating the issue. These microplastics can be ingested by marine organisms and enter the food chain, eventually reaching humans through seafood consumption. The situation is expected to worsen in the coming decades (Kumar *et al.*, 2021; Matavos-

Aramyan, 2024). Henry *et al.* (2019) predicted that by 2050, up to 12 billion tons of plastic waste could accumulate in the oceans, compounding the already significant environmental and health risks. The degradation of plastics also releases harmful chemicals, including toxic additives like plasticizers, flame retardants, and pigments into the environment (Evode *et al.*, 2021; Maddela *et al.*, 2023; Rani *et al.*, 2023). These substances can leach into soil, water, and food sources, posing risks to both wildlife and human health. As these chemicals enter ecosystems, they have the potential to disrupt hormonal systems, cause long-term health issues, and contaminate vital resources. The growing plastic waste crisis calls for urgent and sustained action. Solutions must include enhancing recycling efforts, reducing plastic consumption, and developing environmentally friendly alternative materials.

Hidayah and Syafrudin (2018), Maddela *et al.* (2023), and Novakovic *et al.* (2023) identified seven common types of plastics that are most commonly used: Polyethylene Terephthalate (PET or PETE), High-Density Polyethylene (HDPE), Polyvinyl Chloride (PVC), Low-Density Polyethylene (LDPE), Polypropylene (PP), Polystyrene (PS or Styrofoam), and miscellaneous plastics. These materials are widely used across industries due to their versatility, durability, and low cost. However, their long-lasting nature also leads to significant waste accumulation, especially when these plastics are not properly disposed of or recycled. One of the most concerning environmental impacts of plastic waste is the formation of microplastics, tiny plastic particles that result from the breakdown of larger plastic items over time. To tackle the escalating problem of plastic waste, more effective waste management strategies are crucial. One such strategy is the reduction of unnecessary packaging, which could help minimize the overall amount of plastic waste generated. As described by Ali *et al.* (2022), Ghodke *et al.* (2022), Jeswani *et al.* (2021), and Mirkarimi *et al.* (2022), pyrolysis involves heating plastic waste to high temperatures between 400 °C and 1000 °C in the absence of oxygen. This process breaks down long-chain polymer molecules into smaller, less complex molecules, which can then be used as valuable byproducts such as liquid fuels or wax. A significant advantage of pyrolysis is that it operates without combustion, reducing harmful emissions typically associated with traditional waste disposal methods. By converting plastic waste into useful products, pyrolysis not only helps to address the growing plastic waste problem but also contributes to

sustainable waste management practices. This method offers a potential solution to the environmental burden of plastic waste while providing an alternative source of energy and raw materials.

Recent studies have highlighted the potential of plastic-derived diesel fuels, which primarily consist of hydrocarbons in the C6–C40 carbon range, as an environmentally friendly alternative to conventional diesel. These fuels have shown promise for use in a wide range of diesel engines, from light-duty passenger vehicles to heavy-duty industrial and marine equipment (Dahlbo *et al.*, 2018; Ikäheimo *et al.*, 2019; Liu & Tao, 2022). The carbon range of C6–C40 is well-suited for diesel engine requirements, meaning these plastic-derived diesel fuels could be used without requiring significant modifications to existing engine designs. In addition to transportation, these fuels also have the potential to be utilized in stationary applications such as boilers, furnaces, and turbines, offering a flexible solution for converting plastic waste into useful energy (Koumpakis *et al.*, 2024; Rani *et al.*, 2023). This provides a dual benefit: reducing plastic waste while addressing the growing demand for alternative energy sources. However, despite the advantages, the use of plastic-derived diesel fuels in diesel engines raises concerns about the emissions they produce. Diesel engines typically emit more pollutants compared to gasoline engines, including NO_x, PM, and CO₂, all of which contribute to air pollution, climate change, and health problems (Deng *et al.*, 2020; Gordon *et al.*, 2014; Ibeto & Ugwu, 2019). The level and nature of these emissions can be influenced by the operating conditions of the engine, such as speed and load, making it crucial to evaluate these variables when assessing the environmental impact of plastic-derived diesel fuels. Given the growing interest in plastic-derived diesel fuels, further research is needed to better understand their combustion characteristics and emission profiles in diesel engines. By examining how factors such as load and engine speed affect emissions, researchers can optimize the use of these alternative fuels to minimize their environmental impact. This knowledge is essential for ensuring that plastic-derived diesel fuels provide a viable and sustainable solution for energy production while helping to reduce the harmful effects of plastic pollution.

Building on the need for innovative solutions to tackle environmental challenges and optimize resources, machine learning stands out as a powerful tool. Its ability to analyse complex data and provide actionable insights makes it invaluable for advancing research in sustainable energy and reducing emissions. Machine learning (ML) has garnered significant attention in recent years due to its remarkable ability to process and analyse vast amounts of data, delivering accurate predictions and informed decisions (Gukov *et al.*, 2024; Janiesch *et al.*, 2021; Shaziayani *et al.*, 2022; Yu *et al.*, 2023). Several factors are driving this growing interest in machine learning: 1) Big Data: The exponential growth of digital data has made machine learning an essential tool for extracting meaningful insights and deriving value from massive datasets, which would be impossible to analyse manually. 2) Automation: Machine learning enables the automation of complex tasks that traditionally require human intervention, enhancing operational efficiency and reducing errors across industries. 3) Personalization: ML algorithms excel in creating personalized experiences by analyzing user behavior and preferences. Applications range from recommending products and services to tailoring content for individual users. 4) Predictive Analytics: By identifying patterns in historical data, machine learning can make reliable predictions about future events, such as customer behavior, market trends, or system failures, helping organizations make proactive decisions. 5) Improved Accuracy: ML algorithms often outperform traditional statistical methods and human intuition in tasks like fraud detection, image recognition, and natural language processing, offering higher precision and reliability. 6) Cost Efficiency: As machine learning tools and techniques evolve, they become more accessible and cost-effective, enabling broader adoption across industries and organizations, including smaller businesses with limited resources. These advantages position machine learning as a transformative technology across sectors, from healthcare and finance to retail and manufacturing, where its applications are helping organizations improve decision-making, optimize operations, and create innovative solutions (Janiesch *et al.*, 2021; Kigo *et al.*, 2023; Sarker, 2021).

Artificial Neural Networks (ANN) have gained significant attention in recent years for their ability to process complex, nonlinear relationships within data, making them highly effective for predictive modeling (Swathe *et al.*, 2025; Urooj & Nasir, 2024; Zhang *et al.*, 2025). This is particularly relevant in the context of NO_x emission

prediction in diesel engines, where emissions are influenced by a variety of interconnected factors, including engine load, speed, combustion temperature, fuel type, and operating conditions. Inspired by the structure and functionality of the human brain, ANN employs layers of interconnected neurons to identify hidden patterns and relationships within data (Bernal *et al.*, 2019; B. Yu *et al.*, 2023). Among the different ANN architectures, the Multi-Layer Perceptron (MLP) is one of the most widely used for predictive tasks. An MLP consists of an input layer, one or more hidden layers, and an output layer, enabling it to learn from complex datasets and generalize its predictions (Jin *et al.*, 2022). For NO_x emission prediction, MLP can utilize input parameters such as engine specifications, fuel properties, and operating conditions to provide accurate and reliable results (Din *et al.*, 2024; Viana *et al.*, 2023). This approach is particularly important when studying alternative fuels such as those produced from the pyrolysis of plastic waste. While these fuels present a sustainable alternative to traditional fossil fuels, understanding their impact on NO_x emissions is crucial to ensure they meet environmental standards. By applying MLP models, the capability for NO_x emissions prediction with high precision, while also optimizing engine performance and fuel blends to reduce emissions. Incorporating ANN methods into emissions research offers a powerful tool for addressing global challenges related to air pollution and climate change while supporting the transition to cleaner and more sustainable energy solutions.

In conclusion, the increasing challenges of energy demand, environmental pollution, and plastic waste underscore the urgent need for innovative and sustainable solutions. Transforming plastic waste into diesel-like fuels through pyrolysis offers a promising dual benefit of effective waste management and energy recovery. However, the use of these alternative fuels in diesel engines raises critical concerns about emissions, particularly NO_x emissions, which significantly affect air quality and public health. To address these issues, machine learning techniques, particularly ANN-like MLP, have proven to be powerful tools. Their ability to model complex and nonlinear relationships enables accurate prediction of NO_x emissions, providing valuable insights for optimizing engine performance and fuel blends. By integrating advanced technologies with alternative energy sources, it can pave the way for cleaner, more

sustainable energy systems while minimizing environmental impacts (Calero *et al.*, 2023; Kartsan *et al.*, 2024; Lane, 2019; Saha *et al.*, 2024).

1.2 Problem Statement

Plastic pollution is one of the most serious environmental problems, with thousands of tons generated each year. The lack of suitable methods to dispose of plastic waste has resulted in a negative impact on the environment and ecology, including mass pollution on land, in aquatic habitats, as well as marine biomes. Plastic waste degrades very slowly in the environment, remaining for hundreds of years and disrupting ecosystems at all levels (Khan, 2021; Kruse *et al.*, 2023). Existing practices involving landfilling, recycling, and incineration are not keeping pace with the increase in plastic waste. Landfilling takes up precious land space and leaches out poisonous chemicals into the soil, which in turn causes groundwater pollution (Meng *et al.*, 2024; Zhang *et al.*, 2025). Burning rubbish is another way to reduce the amount of waste heading for landfill, but the fumes from incineration contain air pollutants. Larger plastic items break into microplastics, which have invaded the food chain and drinking water supplies, as well as air, causing potential toxicological effects on both wildlife and humankind (Blazsó, 2006; Maddela *et al.*, 2023). This aspect of these challenges hints at the need for more innovative and sustainable reducing, managing, and repurposing solutions for plastic waste by introducing the pyrolysis process.

The growing demand for alternative and sustainable fuels has led to increased research on biodiesel and plastic-derived diesel fuels as potential substitutes for conventional fossil diesel. Biodiesel produced from renewable sources is recognised for its environmental benefits, including lower GHG emissions and biodegradability. Similarly, plastic-derived diesel fuels that were obtained through the pyrolysis of waste plastics provide an innovative approach to managing plastic waste while contributing to energy sustainability. Despite their potential, both biodiesel and plastic-derived diesel fuels exhibit significant variations in chemical composition, energy content, viscosity, and elemental characteristics, all of which can directly affect their performance and emission levels. One of the key challenges in adopting these

alternative fuels is the lack of comprehensive knowledge regarding their physicochemical properties in comparison to conventional diesel. Biodiesel generally contains a higher oxygen content, which influences combustion efficiency and emission patterns, while plastic-derived diesel fuels may include aromatic and hydrocarbon compounds with unknown effects on combustion and emissions. Variations in functional groups, energy density, molecular structure, and fuel stability necessitate detailed fuel characterization to determine their suitability for diesel engine applications. To address this issue, systematic fuel characterization is crucial to establish the fundamental properties of biodiesel and plastic-derived diesel fuels, including FTIR, bomb calorimetry, kinematic viscometry, GC-FID, and CHNS elemental analysis.

The increasing global demand for sustainable and environmentally friendly fuels has led to extensive research on alternative fuel sources such as palm oil methyl ester and plastic-derived diesel fuels. Despite their potential benefits, their impact on diesel engine performance and emissions remains an area of concern. Differences in chemical composition, energy content, viscosity, and oxygen content may significantly influence engine efficiency, fuel consumption, and pollutant emissions, which could affect their feasibility for widespread application in diesel engines. Plastic-derived diesel fuel presents a novel solution for addressing both energy needs and plastic waste management. Its combustion properties, stability, and long-term effects on engine components remain largely unexplored. The presence of aromatic hydrocarbons and impurities in plastic-derived diesel may influence combustion efficiency, engine wear, and pollutant formation, raising concerns about its suitability for diesel engine applications. There remains a lack of comprehensive studies comparing the performance and emissions of diesel engines using pure diesel, biodiesel, and plastic-derived diesel fuels under similar operating conditions. The variations in BP, BTE, and BSFC must be thoroughly investigated to determine the efficiency of these fuels in diesel engine operations. Additionally, their impact on exhaust emissions, including CO, CO₂, NO_x, and HC, needs to be assessed to ensure compliance with environmental and regulatory standards.

NO_x emissions from diesel engines are a significant environmental and health concern, contributing to air pollution, smog formation, and respiratory diseases. The generation of NO_x is influenced by multiple nonlinear factors, including engine operating conditions, fuel composition, combustion temperature, AF ratio, and injection timing. When analysing emission trends based on exhaust emission standards, NO_x emissions demonstrate the most significant reduction compared to other pollutants. The introduction of alternative plastic-based fuels as a potential substitute for conventional diesel further complicates the emission behaviour, thus requiring advanced predictive modelling techniques. Conventional linear models and empirical correlations often struggle to accurately capture the complex interactions governing NO_x formation, leading to limitations in prediction accuracy. To address this issue, this study aims to develop a non-linear predictive model using an MLP neural network to forecast NO_x emissions from diesel engines operating on various fuel blends from plastic-derived alternatives and biodiesel. To optimize the model's performance, multiple training algorithms were applied and compared, including Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). The predictive capability of these models was assessed using performance metrics such as Root Mean Squared Error (RMSE), Normal Absolute Error (NAE), and Coefficient of Determination (R^2) to determine the most accurate and reliable model for NO_x emissions prediction. Conventional linear models and empirical correlations often struggle to accurately capture the complex interactions governing NO_x formation, leading to limitations in prediction accuracy. To address this issue, this study aims to develop an MLP neural network to forecast NO_x emissions from diesel engines operating on various fuel blends from plastic-derived alternatives and biodiesel. By leveraging the ability of MLP to model nonlinear relationships and optimizing its training process, this research aims to develop a robust predictive tool for emissions estimation.

The use of alternative fuels from plastic-derived fuels adds complexity to the diesel combustion process, affecting emissions in ways that are not fully understood. Current predictive models often fall short when it comes to accounting for the unique variations and nonlinear behaviour of these new fuels, creating an urgent need for more advanced modelling techniques. ANN offers a promising solution as it excels at

capturing complex, nonlinear relationships and can learn directly from experimental data (Sun *et al.*, 2024). ANN can efficiently process large datasets, adapt to changes in engine conditions, and deliver accurate predictions of NO_x emissions under varying circumstances. This research taps into the power of ANN to overcome the limitations of existing models. The goal is to develop a robust and reliable model that accurately predicts NO_x emissions considering the dynamic nature of diesel combustion and the distinct characteristics of alternative fuels (Kumar *et al.*, 2024). By enhancing the accuracy of emission predictions, this model helps to better understand emissions behaviour and improve diesel engine performance.

Plastic pollution poses a significant environmental threat, imposing innovative solutions such as pyrolysis to convert plastic waste into alternative fuels. The rising demand for sustainable energy has driven research into biodiesel and plastic-derived diesel fuels as viable substitutes for conventional diesel. However, variations in their chemical composition, combustion properties, and emissions underscore the need for comprehensive fuel characterization and performance assessment in diesel engines. A critical challenge in adopting these alternative fuels is their impact on NO_x emissions, a major contributor to air pollution. NO_x formation is governed by complex nonlinear interactions, making conventional predictive models inadequate for accurate estimations. To address this, this study employs an MLP neural network, optimizing its predictive capabilities through advanced training algorithms. By leveraging the ability of ANN to model nonlinear relationships, this research enhances the accuracy of NO_x emissions forecasting, improving the understanding of combustion dynamics in diesel engines operating with alternative fuels. This study contributes to both sustainable waste management and cleaner energy solutions. The findings provide valuable insights into fuel performance, emissions control, and predictive modelling, supporting the integration of plastic-derived diesel into energy systems while advancing emission reduction strategies for diesel engines.

1.3 Aims and Objectives

This research aims to investigate the effects of different types of plastic-derived diesel fuels and various engine operating parameters, such as load and speed, on the performance and emissions of a diesel engine. It seeks to develop predictive models to assess and forecast air pollution associated with these fuels. To address these goals, four specific objectives have been outlined.

The specific objectives of this research are as follows:

1. To characterize the fuel properties of plastic-derived diesel fuels by different methods of Fourier transform infrared spectroscopy, bomb calorific value, kinematic viscometer, gas chromatograph flame ion detector, and CHNS elemental analysis.
2. To investigate the performance and emissions of diesel engines using pure diesel, palm oil methyl ester biodiesel, and plastic-derived diesel fuels.
3. To develop non-linear models for predicting NO_x emissions from the diesel engine.
4. To establish the best-fitted model for NO_x emissions prediction from diesel engines through performance indicators.

1.4 Scope of Research

This research focuses on the performance and emissions of a small diesel engine, specifically the Yanmar L48N6-MTMYI located at the Engine and Power Plant Laboratory at Universiti Malaysia Terengganu. The research investigates the effects of various plastic-derived diesel fuels and engine operating conditions, including load, speed, and fuel type, on engine performance and exhaust emissions. The research is designed around two key sets of variables: dependent and independent. The independent variables include engine load, speed, torque, fuel type, and power output, which are all essential factors influencing engine performance. The dependent variables focus on exhaust emissions, specifically CO, CO₂, HC, NO_x, and NO₂. Unfortunately, PM emissions were not measured due to the lack of a PM sensor in the

gas analyzer SPTC GP-20G used for the research. Additionally, combustion parameters were not included in the analysis due to the unavailability of certain maintenance parts for the engine.

The research utilizes a range of fuel types for testing, including pure diesel (B0), a 10% biodiesel blend from palm oil methyl ester (B10), and two plastic-derived diesel fuels that are high-density polyethylene (HDPE10) and polypropylene (PP10). These fuels were supplied by Syngas Sdn. Bhd. to ensure the availability of alternative fuel sources for the engine tests. The engine's operational conditions were varied to include different load levels (10%, 25%, 50%, 75%, and 100%), following the standard ISO 8178 D2 for diesel engine experimental tests. The engine speeds were tested at two levels: 2000 rpm and 2500 rpm, as the engine is not designed to operate at its maximum rated speed of 3600 rpm. The engine manufacturer advises against running the engine at this maximum speed. The exhaust emissions from the engine were measured using an Autochek Gas Analyzer SPTC GP-20G, which automatically records CO, CO₂, HC, NO_x, and O₂ levels. Emission measurements were taken several minutes after the engine had completed its warm-up cycle and reached a steady operating condition. This ensured that the data collected accurately reflected the engine performance under typical operational conditions.

By combining the collected data from various operating conditions and fuel types, the research aims to develop non-linear models that can predict the impact of different fuels and engine settings on emission levels and overall engine performance. A total of nine input variables were used to predict NO_x emissions concentrations: speed, torque, power, BSFC, fuel rate, and emissions such as CO, CO₂, HC, and O₂ production. Three training algorithms were compared in this study: LM, BR, and SCG training algorithms. The model performance was evaluated using three performance indicators (PI): root mean square error (RMSE), Coefficient of Determination (R^2), and normalized absolute error (NAE). These PIs were selected to assess the accuracy and robustness of the prediction. No other PI, such as mean square error (MSE), mean absolute percentage error (MAPE), or adjusted R^2 , was considered for this model evaluation. This research is limited to the use of these specific algorithms and PIs and

does not extend to alternative machine learning models or other statistical performance indicators.

This contributes to a deeper understanding of how alternative fuels, particularly plastic-derived fuels, can be used in diesel engines to reduce environmental impacts while also optimizing engine performance for various industrial applications. This research is particularly relevant for Malaysia, where plastic waste accumulation and diesel dependency remain critical issues. Utilizing locally sourced plastic-derived fuels offers a dual benefit of waste reduction and energy diversification for industrial and rural applications.

1.5 Significance of Research

This research plays a crucial role in addressing two pressing global issues: plastic pollution and the search for sustainable fuel alternatives to conventional fossil fuels. While there has been extensive research into alternative fuels aimed at reducing emissions and improving engine performance, few studies have specifically focused on plastic-derived diesel fuels concerning the Yanmar L48N6 diesel engine. This gap highlights the need for further investigation into how different types of plastic-derived fuels perform in diesel engines under varying operating conditions, such as changes in load and speed. The goal of this research is to explore the influence of different blended plastic-derived fuels impact engine performance and emissions in the Yanmar L48N6 engine with a focus on providing insights that could be applied to similar engine models. Additionally, this research aims to develop machine learning models, specifically MLP models, to predict the effects of different engine operating conditions and fuel types. By analysing the relationships between different variables, this research creates predictive models that can optimize engine performance and minimize emissions, thus offering valuable tools for both engine manufacturers and fuel producers.

Many emission measurement devices do not have NO_x sensors due to high costs, maintenance difficulties, and limited availability, making predictive NO_x

modelling a valuable alternative. Traditional NO_x sensors are expensive and require frequent calibration, which can be difficult for industries trying to follow stricter environmental laws. Instead, predictive modelling uses easily measurable factors like engine load, temperature, and air-fuel ratio to estimate NO_x emissions cost-effectively and efficiently. Using ANN and ML, NO_x modelling can predict emissions in real time based on engine conditions, fuel type, and combustion characteristics. This is especially useful because different fuels from biodiesel, synthetic fuels, and pyrolysis plastic fuels produce different amounts of NO_x. A well-designed NO_x prediction model can adapt to these fuel differences, helping researchers develop cleaner and more efficient fuel alternatives. Predictive NO_x models also help in reducing emissions by optimizing engine settings, exhaust gas recirculation (EGR), and fuel injection timing. Many modern diesel and gasoline vehicles use NO_x modelling within their Engine Control Units to meet strict emission regulations like Euro 6 and EPA limits, avoiding the need for expensive and high-maintenance sensors. Similarly, power plants use computer-based models to estimate NO_x emissions instead of installing costly sensors in extreme conditions. This study provides a practical, affordable, and adaptable way to estimate NO_x emissions, helping industries meet environmental regulations while developing cleaner and more efficient engine technologies.

The evolution of emission standards for non-road diesel engines demonstrates a clear regulatory trend toward stricter NO_x emission limits, highlighting the increasing importance of NO_x prediction and reduction strategies. Among the key regulated pollutants, NO_x has undergone the most significant reductions over time, reflecting its dominant role in air pollution, acid rain, and adverse health effects such as respiratory illnesses. This stringent focus on NO_x emissions has motivated the development of advanced emission control technologies and predictive modelling approaches to ensure compliance with tightening environmental regulations. Such aggressive reductions demand highly accurate monitoring and control strategies since even minor deviations from permitted NO_x levels can lead to regulatory non-compliance, financial penalties, and operational inefficiencies. Traditional NO_x measurement methods using sensors can be costly and require frequent calibration, making predictive NO_x modelling an essential alternative. By ANN application and ML models, NO_x emissions can be estimated in real time based on engine operating conditions, fuel

composition, and combustion parameters, reducing the reliance on expensive sensors while maintaining accuracy. A reliable NO_x prediction model can help optimize fuel blends and engine settings, and ensure adaptability to alternative fuels to achieve lower NO_x emissions without compromising performance.

1.6 Overview of Thesis

The thesis begins with the background of the research and further describes the problems associated with exhaust emissions, plastic waste generation, and energy depletion. This is followed by the research objectives, research scope, and significance of the research. The chapter also clarifies the structure of the thesis and gives an overview of the main points of the thesis. The author then embarks on a comprehensive literature review on the pyrolysis process, biodiesel and its properties, production methods, and its effect on engine performance and emissions. The application of machine learning to predict the exhaust emissions from engines is also investigated. The author then describes the experimental setup and methodology used to carry out the research, which involves running the diesel engine on different blends of biodiesel, pure diesel, and plastic-derived diesel fuels. The experimental results are presented and analysed in detail, including engine performance parameters such as power output, torque, fuel consumption, and emissions of CO, CO₂, NO_x, and HC. The author also compares the experimental results with those obtained from using conventional diesel fuel. Lastly, the ANN analysis was done to obtain predictive modelling of NO_x emissions through training and testing.

CHAPTER 2

LITERATURE REVIEW

The chapter begins with discussions of the current state of managing plastic waste and the potential for energy generation from it. It covers a range of topics, including the pyrolysis process and the status of biodiesel in Malaysia. Additionally, the properties and characteristics of plastic fuel and biodiesel, their respective production methods, and their impact on engine performance and emissions are discussed. The chapter also explores engine emissions formation, emissions guidelines, air quality regulations, and engine performance. Finally, the potential of machine learning to predict future trends and its applicability in this area are examined in the concluding section of the chapter.

2.1 Overview of Plastic Waste Management

Plastic is a remarkable material known for its lightweight nature, resistance to corrosion and chemicals, mechanical strength, and durability. These qualities have made plastic an essential material across various industries, including packaging, construction, automotive, electrical, and electronics (Qureshi *et al.*, 2020; Rafey & Siddiqui, 2023; Wang *et al.*, 2022). However, its widespread use has come at a significant environmental cost. Since the 1950s, global plastic production has reached an estimated 6300 million tons, with a large portion ending up in landfills or the environment, particularly in oceans, which serve as the largest repository of plastic waste (Geyer *et al.*, 2017; Wang *et al.*, 2022). The accumulation of plastic waste in the oceans poses a severe threat to marine ecosystems and biodiversity. Marine animals,

including sea turtles, birds, and fish, often become entangled in plastic debris, leading to injuries, restricted movement, suffocation, or even death. Furthermore, many species ingest plastic debris, mistaking it for food. This ingestion can cause digestive blockages, malnutrition, and exposure to toxic substances released by plastics, ultimately resulting in fatal consequences (Khan, 2021; Kruse *et al.*, 2023; Peng *et al.*, 2024).

Beyond visible pollution, microplastics in tiny fragments formed by the breakdown of larger plastic items present a hidden and growing concern. These microplastics have been found in marine organisms, entering the food chain and potentially impacting human health through seafood consumption. Airborne microplastics also contribute to environmental pollution, with evidence suggesting potential risks to human respiratory health (Hidayah & Syafrudin, 2018; Maddela *et al.*, 2023). The global response to managing plastic waste has been inconsistent and often inadequate. Traditional methods like landfilling and incineration dominate waste management practices. But these methods are far from sustainable. Landfills contribute to long-term environmental degradation, while incineration generates GHG and releases toxic pollutants, exacerbating climate change and air quality issues (Henry *et al.*, 2019; Meng *et al.*, 2024; Zhang *et al.*, 2025). In recent years, innovative approaches to plastic waste management have emerged as viable solutions. One such approach is the conversion of plastic waste into alternative fuels through pyrolysis. This process involves heating plastics in the absence of oxygen, breaking them down into smaller hydrocarbon molecules, and creating usable fuels. Pyrolysis not only addresses the problem of waste accumulation but also provides a renewable energy source and reduces dependence on conventional fossil fuels (Ali *et al.*, 2022; Jeswani *et al.*, 2021).

Plastic waste not only creates visible environmental pollution but also poses significant indirect risks to human health and contributes to global environmental challenges. As plastics degrade, they fragment into microplastics and nanoplastics, which release toxic additives and chemicals into the surrounding environment. These substances, such as bisphenol A (BPA), phthalates, and polybrominated diphenyl ethers (PBDEs), can leach into soil, water, and air, ultimately entering the food chain

(An *et al.*, 2021; Barboza *et al.*, 2018; Yuan *et al.*, 2022). BPA has been widely studied and is linked to endocrine disruption, reproductive health issues, developmental disorders, and even certain types of cancer. These toxicants accumulate within organisms and magnify their effects as they move up the food chain, eventually impacting human health through contaminated food and water (Mukherjee *et al.*, 2021; Ohore & Songhe, 2019). Beyond health risks, plastic waste also significantly contributes to climate change. Incinerating plastic waste releases large quantities of CO₂ and other potent GHGs such as methane and nitrous oxide, depending on the combustion conditions. Moreover, incomplete combustion during incineration can produce toxic pollutants like dioxins and furans, which are hazardous to both humans and the environment. These emissions exacerbate global warming and pose serious health risks, especially in areas near incineration facilities (Geyer *et al.*, 2017; Meng *et al.*, 2024; Zhang *et al.*, 2025).

The environmental footprint of plastics begins even before their disposal. The production of plastics is heavily reliant on petrochemicals derived from fossil fuels such as crude oil and natural gas. Extracting and processing these materials is energy-intensive and results in substantial GHG emissions. Current trends suggest that by 2050, the plastic industry could consume up to 20% of the world's oil supply, highlighting its substantial contribution to global fossil fuel dependency (Henry *et al.*, 2019; Maddison *et al.*, 2023). In addition to production and disposal, the transportation of plastic waste adds to its carbon footprint. Waste is often shipped over long distances to recycling facilities, landfills, or incineration plants, requiring significant energy and emitting GHGs. Unfortunately, the inefficiency of global recycling systems means that much of this waste ends up in landfills or leaks into the environment, causing ecological harm and biodiversity loss. This leakage not only pollutes ecosystems but also facilitates the widespread distribution of microplastics in air, water, and soil, exacerbating the issue further (Jeswani *et al.*, 2021; Khan, 2021). Addressing these indirect effects of plastic waste requires a multi-faceted approach. Effective waste management practices, the adoption of sustainable materials, and global policy interventions are essential to mitigate the risks associated with plastic waste. Without significant changes, the cumulative impacts of plastic waste on human health,

ecosystems, and climate stability continue to escalate, presenting severe long-term challenges.

Like many countries around the world, Malaysia faces significant challenges in managing its plastic waste, which continues to grow in both volume and impact. According to the Malaysia Investment Development Authority (MIDA), the nation generated approximately 38,427 metric tons of solid waste daily in 2021, with a per capita waste generation rate of 1.17 kg per day. This rate is slightly higher than the ASEAN guideline of 1.14 kg per capita per day, indicating that waste management efforts require urgent attention (MIDA, 2023). In 2020, the composition of waste was dominated by food waste (16,415 metric tons per day), plastic waste (5,779 metric tons per day), and paper and cardboard waste (4,197 metric tons per day). A staggering 90.6% of the waste generated was municipal solid waste (MSW), which includes household, commercial, and institutional waste. Despite efforts to manage this waste, the disposal methods remain concerning. Landfills account for the largest portion of waste disposal at 79.4%, followed by incineration (13.5%), and recycling, which only accounted for 6.8% of the total waste processed worldwide (Wojnowska-Baryła *et al.*, 2022). These figures highlight overreliance on landfills, which are not only unsustainable but also contribute significantly to environmental degradation and GHG emissions.

A closer look at waste generation in Terengganu, specifically Kuala Terengganu, paints a similar picture. In 2019, the city generated approximately 432.69 tons of solid waste daily, amounting to 158,131.85 tons over the year. Of this waste, food waste made up nearly half (49.3%), followed by plastic waste at 16.7%, and paper waste at 8.8%. Other categories included metal (7.8%), garden (7.2%), glass (5.9%), and textile waste (4.3%) (Alias *et al.*, 2021). This waste composition underlines the significant role plastic plays in the waste stream. The growing volume of plastic waste in Malaysia, especially in urban centers like Kuala Terengganu, has serious environmental and health implications. Plastic waste is particularly problematic due to its durability and leading to long-term environmental contamination. When plastic waste enters natural environments, particularly oceans, it causes harm to marine life through entanglement, ingestion, and chemical contamination, which affects the entire

ecosystem, including humans who rely on marine resources. Moreover, the production and disposal of plastic contribute to climate change, with plastic production requiring significant fossil fuel resources and plastic incineration releasing harmful GHG into the atmosphere (Geyer *et al.*, 2017; Maddela *et al.*, 2023). Given the volume of plastic waste generated and the challenges in managing it, there is an urgent need for innovative solutions. This includes improving recycling systems, enhancing waste-to-energy technologies, and exploring alternative uses for plastic waste to reduce the burden on landfills and the environment.

In 2020, Malaysia's recycling rate was 17.5%, which shows a modest improvement from the previous year and remains significantly lower than many other countries. The National Environment Agency (NEA) verified that Singapore achieved a recycling rate of 57% in 2019, and other developed countries like Germany and Sweden have reached recycling rates exceeding 60% and 70%, respectively (NEA, 2023). This stark contrast highlights the need for Malaysia to accelerate its recycling efforts to match global standards. Several factors contribute to the low recycling rate, such as the primary challenges being the inadequate infrastructure and facilities for effective waste sorting and recycling (Mubaroq *et al.*, 2024). Without well-established systems for separating recyclables at the source and processing them efficiently, much of the waste ends up in landfills or is incinerated. Public awareness and education about the importance of recycling are still limited, and many individuals do not fully engage in recycling programs. The lack of strong incentives or comprehensive regulatory frameworks to promote recycling further hampers progress. While other nations have successfully implemented policies and incentives to encourage recycling, the regulatory landscape in this area remains underdeveloped (Dahlbo *et al.*, 2018; Mirkarimi *et al.*, 2022; Qureshi *et al.*, 2020). As of 2020, Malaysia had 2,636 registered waste management facilities, with landfills making up 51.2% of the total. This heavy reliance on landfills, coupled with the increasing volume of waste, worsens environmental issues, particularly plastic pollution. To improve recycling rates and reduce plastic pollution, Malaysia needs to invest in better waste sorting systems, increase public awareness campaigns, and introduce more robust regulations and incentives. A holistic approach combining government action, infrastructure improvements, and public participation should be key to addressing the plastic waste

problem and moving towards a more sustainable waste management system in Malaysia (Alias *et al.*, 2021; Chen *et al.*, 2021; Chin *et al.*, 2022).

2.2 Energy Production Potential from Plastic Waste

Pyrolysis has emerged as a highly promising method for converting plastic waste into valuable energy products, helping to address both the mounting plastic waste problem and the growing demand for renewable energy. The products derived from pyrolysis, particularly the liquid fuel, can serve as a replacement for conventional diesel or gasoline, while the gases produced can be used for power generation. By utilizing pyrolysis, plastic waste can be reduced significantly, but also create a sustainable energy source, making it an attractive solution in the context of circular economy initiatives. The European Union's Waste Framework Directive sets clear guidelines for waste management and recovery practices, including the use of pyrolysis for energy recovery. This directive outlines four key principles that should govern waste management activities: 1) waste management must not endanger human health or the environment, 2) it must not harm soil, plants, animals, or water, 3) it should minimize disturbances, such as excessive noise or odors, and 4) it must avoid damaging landscapes or protected areas (Ritchie & Rosado, 2017; Wang *et al.*, 2022). These principles ensure that pyrolysis and similar processes are carried out in an environmentally responsible manner, making the technology both safe and effective for waste-to-energy applications. In line with these regulations, pyrolysis offers a dual benefit, helping to manage plastic waste while providing a renewable source of energy. As the world grapples with the environmental impact of plastic pollution and the urgent need for sustainable energy solutions, pyrolysis stands out as a viable and environmentally friendly method to repurpose waste materials into energy.

The recycling industry and waste management systems face several ongoing challenges, particularly when it comes to processing and utilizing plastic waste effectively. One significant issue is that much of the easily recyclable plastic has already been processed, leaving behind more difficult-to-recycle materials. The market for secondary raw materials remains underdeveloped, with limited demand for

recycled plastics (Arijeniwa *et al.*, 2024; Koumpakis *et al.*, 2024). This is compounded by the fact that recycled materials often cost more than new and virgin materials, making it less attractive for industries to use recycled plastics (Torkelis *et al.*, 2024). As a result, there is an urgent need for innovative technologies that can make recycling both economically viable and sustainable. Advancements in technology related to waste collection, sorting, and recycling processes could help improve efficiency and increase the use of recycled plastics in new products. New sorting technologies, automated collection systems, and more efficient recycling methods could lower the costs of recycling and make it more appealing to industries (Babaremu *et al.*, 2024; Sánchez-García *et al.*, 2024; Vuppaladadiyam *et al.*, 2024). However, traditional mechanical recycling processes are limited in their ability to meet the growing demand for high-quality recycled plastics. To address these limitations, feedstock recycling technologies are emerging as a promising alternative. Unlike mechanical recycling, which typically breaks plastics into smaller pieces, feedstock recycling processes plastic waste back into its original monomers or basic building blocks. This approach offers the potential for recycling plastics into high-quality raw materials that can be reused in manufacturing, making it a more sustainable and efficient method for processing plastic waste. The development of feedstock recycling technologies is crucial for meeting future recycling demands and ensuring that plastics can be continually reused in a circular economy (Babaremu *et al.*, 2024; Calero *et al.*, 2023; Vuppaladadiyam *et al.*, 2024).

The recycling industry and waste management systems face significant challenges in addressing the growing plastic waste problem. A key issue is that most of the easily recyclable plastics have already been processed, leaving behind more difficult-to-recycle materials. The market for secondary raw materials is underdeveloped, and the prices of recycled materials are often higher than those of primary raw materials. This economic barrier makes it less attractive for industries to use recycled plastics in production, which limits the overall effectiveness of recycling efforts (Adekanmbi *et al.*, 2024; Seier *et al.*, 2024; Zambrano *et al.*, 2024). As a result, there is a clear need for innovative recycling technologies that can overcome these economic challenges and make recycled plastics more competitive with virgin materials. To address these challenges, technological advancements in areas such as

waste collection, sorting, and recycling processes are crucial. Such innovations could improve the efficiency of recycling operations, reduce costs, and make recycled plastics more appealing for use in manufacturing new products. As these technologies develop, they hold the potential to create a more sustainable and economically viable recycling system, one that encourages wider adoption of recycled plastics and helps reduce dependence on raw and virgin materials (Babaremu *et al.*, 2024; Sánchez-García *et al.*, 2024; Vuppaladadiyam *et al.*, 2024). However, traditional mechanical recycling that involves breaking plastics down into smaller pieces for reuse is reaching its limits. This method can degrade the quality of the materials, making them less suitable for certain applications. In response, feedstock recycling technologies are gaining attention. Unlike mechanical recycling, feedstock recycling breaks plastics down into their original monomers, which can then be used to create new plastics of higher quality. This approach holds promise for maintaining the integrity of the material, enabling it to be recycled more efficiently and repeatedly. Feedstock recycling could be a game-changer, meeting the growing demand for high-quality recycled plastics and reducing the need for virgin plastic production (Babaremu *et al.*, 2024; Calero *et al.*, 2023; Vuppaladadiyam *et al.*, 2024).

Unlike traditional incineration, pyrolysis is an eco-friendly technology for recovering energy from plastic waste. It offers a significant reduction in carbon emissions compared to direct combustion (Erdogan & Erdogan, 2020; Jahirul *et al.*, 2021). During pyrolysis, plastics are heated in an oxygen-free environment, causing their long-chain polymers to break down into smaller and simpler molecules. The process occurs at various temperatures depending on the type of plastic, yielding a range of byproducts such as gases, oils, and solid residues. These products can be used for energy generation or further refined, making pyrolysis an effective way to manage plastic waste and recover valuable resources. As shown in Table 2.1, different plastic types, their applications, and the resulting pyrolysis products demonstrate the versatility of this technology. One of the most significant outcomes of pyrolysis is the production of plastic-derived diesel fuels, which have garnered increasing interest in recent years. Each plastic type has distinct properties that make it particularly suited to specific uses. PET is commonly used in bottles and food packaging due to its strength and transparency. PVC is primarily used for insulation and window frames,

owing to its resistance to fire and durability. Similarly, PP is a versatile plastic used in medical devices, car batteries, and carpets, thanks to its heat and chemical resistance, as well as its rigidity and strength.

The unique properties of these plastics, such as chemical resistance, heat resistance, strength, ductility, and transparency, are specifically engineered to meet the demands of the diverse applications they serve. These materials are carefully tailored to provide the necessary performance characteristics for their intended roles, demonstrating the versatility and importance of plastics in modern society. When it comes to recycling, pyrolysis offers a promising method for converting plastic waste into valuable energy products. At lower temperatures (less than 400°C), pyrolysis typically breaks down plastics like HDPE, PP, and PET into lighter hydrocarbons such as waxes and oils. These products can potentially be used as secondary fuels or chemical feedstocks, which provide an alternative source of energy and materials. In contrast, at higher pyrolysis temperatures (more than 700°C), the process yields a wider range of products, including gases like methane and aromatic compounds, as well as light oils and polymer derivatives such as styrene. For certain plastics like PET and PVC, high-temperature pyrolysis can produce valuable chemicals like benzene and formaldehyde, which are significant in chemical manufacturing.

According to Sekar *et al.* (2021) and Venkatesan *et al.* (2023), plastic-derived diesel fuels saw a growth rate of about 58% in 2018. These fuels can either replace conventional diesel or serve as additives in lubricants, offering an alternative energy source that can reduce dependence on fossil fuels. This makes pyrolysis not only a solution to plastic waste but also a step toward more sustainable energy production. In addition to its role in energy recovery, pyrolysis helps mitigate the environmental impact of plastic waste. It prevents the accumulation of waste in landfills and oceans, which is crucial for protecting marine life and ecosystems by converting plastics into fuel and other useful products. Pyrolysis presents a promising method for addressing plastic pollution while contributing to sustainable energy solutions.

Table 2.1 Plastic types, properties, applications, and pyrolysis products (Maddela *et al.*, 2023; Mirkarimi *et al.*, 2022; Novakovic *et al.*, 2023; Qureshi *et al.*, 2020; Scheirs & Kaminsky, 2006)

Plastic types	Properties	Applications	Low-temperature products (<400°C)	High-temperature products (>700°C)
PET	• High chemical and thermal stability • Transparency • Low gas and water vapor permeability • Gas barrier	• Bottles • Food packaging • Electrical insulation • Printing sheets	Terephthalic acid	Benzene, benzoic acid, formaldehyde, and acetaldehyde
HDPE	• Long polymer chain • High crystalline • High strength	• Bottle caps • Chemical storage containers • Food storage containers • Fuel tanks for vehicles	Waxes and oils	Gases and light oils
PVC	• Resistance to fire	• Wire and cable insulation • Packaging • Window frames • Food foil • Medical devices	Hydrochloride and benzene	Toluene
LDPE	• Lower tensile strength and hardness, but better ductility compared to HDPE	• Wrapping foils for packaging • Trash bags • Plastic bags		

PP	● Good heat and chemical resistance ● Low density ● High rigidity ● High hardness	● Medical and laboratory devices ● Piping systems ● Carpets ● Plastic pails ● Car batteries	Waxes and oils	Gases and light oils
PS	● Heat residence ● Good durability ● High strength ● Lightness	● Food packaging ● Construction ● Electronics ● Medical devices ● Clothes hangers	Styrene and its oligomers	Styrene and its oligomer, polyaromatic hydrocarbon
Other	● na	● Plastic CDs and DVDs ● Medical storage containers ● Eyeglasses ● Baby bottles	Di-isocyanate	Methane, aromatics

2.3 Pyrolysis Process and Its Fuel Properties

The rapid growth of plastic production in the polymer industry has profoundly shaped modern life, providing unmatched convenience and versatility across various sectors. Plastics are lightweight, resistant to corrosion and chemicals, and possess high mechanical strength and durability, making them ideal for a wide range of applications. These properties have made plastics indispensable in industries such as packaging, construction, automotive, electronics, and electrical goods, where they contribute to product performance, cost-effectiveness, and durability (Geyer *et al.*, 2017; Mirkarimi *et al.*, 2022; Qureshi *et al.*, 2020). However, the widespread use of plastic has also raised significant environmental and health concerns. Despite their numerous benefits, plastics are non-biodegradable, and their disposal has become a growing problem. As plastic waste accumulates in landfills and oceans, it not only threatens wildlife and ecosystems but also contributes to pollution and climate change. The environmental footprint of plastic, particularly in terms of waste and emissions from its production and disposal, is prompting urgent calls for more sustainable practices (Mei *et al.*, 2019; Mofijur *et al.*, 2019; Rajak *et al.*, 2020; Santhosh *et al.*, 2020). In light of these challenges, the need for innovative solutions to manage plastic waste and reduce harmful emissions is more critical than ever. Researchers are exploring various methods to tackle these issues, including advanced recycling technologies and alternative waste management strategies. One promising approach is the conversion of plastic waste into fuel through a process called pyrolysis (Blazsó, 2006; Qureshi *et al.*, 2020). This method not only helps address the growing plastic waste crisis but also provides a potential solution to the global energy demand. As the world grapples with rising energy consumption and environmental degradation, it is also finding sustainable ways to repurpose plastic waste could play a significant role in both mitigating pollution and meeting future energy needs.

The pyrolysis process has emerged as a highly effective and sustainable method for converting plastic waste into valuable fuels, offering distinct advantages over conventional plastic waste disposal techniques. Pyrolysis involves the thermal decomposition of plastics in the absence of oxygen, typically occurring at temperatures between 300°C and 900°C. This process generates a variety of products, including

liquid fuels, waxes, and gases, depending on the operating conditions (Awang *et al.*, 2022; Mirkarimi *et al.*, 2022; Rajak *et al.*, 2020). Unlike traditional disposal methods such as incineration, which can release harmful pollutants into the atmosphere, pyrolysis presents a more environmentally friendly alternative by transforming plastic waste into usable energy products. The pyrolysis process offers the flexibility to produce different types of fuels and chemicals based on key process parameters like temperature, heating rate, and pressure. Generally, the resulting end products are a mix of liquid hydrocarbons, waxy residues, and gases. The liquid fraction is composed of oils that can be further refined into fuels such as diesel, while the waxy residue can be processed into higher-value products (Alfè *et al.*, 2022; Al-Rumaihi *et al.*, 2022; Shah *et al.*, 2023). By adjusting the conditions, it is possible to optimize the process to produce a desired balance of fuels and chemicals.

One of the significant benefits of pyrolysis over traditional waste management methods is its ability to produce ultra-low-sulphur diesel fuel. This is particularly important as it offers a cleaner alternative to conventional diesel with minimal sulphur content, making it more environmentally friendly. The pyrolysis of plastics, particularly polyolefins like PE and PP, breaks them down into smaller molecules, which can be converted into high-quality diesel fuel and reducing the reliance on fossil fuels. Pyrolysis plays a crucial role in tackling the global plastic waste crisis. Converting plastic waste into usable energy products helps divert plastics from landfills and oceans and minimizes their negative environmental impact. The fuels derived from pyrolysis contribute to a reduction in GHGs, aligning with sustainability goals and supporting the transition to a circular economy (Awang *et al.*, 2022; Mirkarimi *et al.*, 2022). As such, pyrolysis stands out not only as an effective waste-to-energy solution but also as a valuable contributor to environmental protection and sustainable energy production.

The pyrolysis process for converting plastic waste into fuel begins with the preparation of the feedstock. According to Syngas (2021) and as shown in Figure 2.1, the pyrolysis process starts by shredding solid plastic waste into smaller flakes and granules using a shredder machine. These shredded plastics are then pelletized into uniform plastic pellets, which are used as the feedstock for the extrusion machine.

During extrusion, the plastic pellets are subjected to incremental heat, reaching temperatures around 200°C. The current plastics in a softened or molten state are transported through a screw barrel, which directs them into a heated reactor chamber. At this stage, the process operates under normal atmospheric pressure, but the temperature inside the reactor is increased to between 400°C and 900°C. At these elevated temperatures, the plastic undergoes thermal decomposition, breaking down into smaller molecules and transitioning into a gaseous state. During this phase, the gases interact with a catalyst, typically sodium hydroxide (NaOH) or potassium hydroxide (KOH), which aids in further breaking down the polymer chains into simpler compounds (Faraguna *et al.*, 2019; Sanjeevannavar *et al.*, 2022; M. Sarker *et al.*, 2011).

The resulting gaseous products are then directed to a distillation column, where the gases are cooled and undergo condensation. This cooling process results in the formation of liquid fuel. The condensed liquid is stored in a storage tank for later use. The quality of the fuel produced through this process is typically high, with some studies reporting yields of more than 80% of the initial plastic feedstock depending on the type of plastic used and the specific process conditions (Owusu *et al.*, 2018; Palmay *et al.*, 2022; Zhang *et al.*, 2020). This process has demonstrated promising results in producing biofuels from plastic waste. The high yield of liquid fuel suggests that the pyrolysis process could serve as a valuable method for converting plastic waste into sustainable energy and mitigating the environmental impact of plastic waste accumulation.

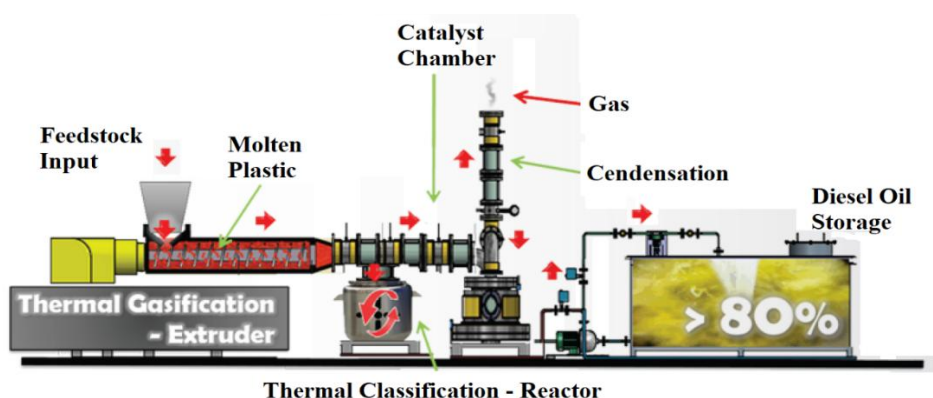


Figure 2.1 Overview of the pyrolysis process (Syngas, 2021). Printed with permission

Table 2.2 Proximate analysis of different types of plastics and fuels (Erdogan, 2020; Ghodke *et al.*, 2022; Surenderan *et al.*, 2018)

	Calorific value (MJ/kg)	Moisture (wt%)	Fixed carbon (wt%)	Volatile (wt%)	Ash (wt%)
PET	24.13	<0.7	6 – 14	85–92	<0.1
HDPE	49.4	<0.3	~0	94–99.8	<1.5
PVC	18	<0.8	5 – 7	58–94.8	<0.1
LDPE	37.4–46.6	<0.3	~0	99–99.8	<0.4
PP	45.3–46.4	<0.4	<1.2	95–99.6	1 – 4
PS	37.7–42.1	<0.3	<0.2	99–99.8	<0.5
Other	-	<0.2	<3	97–99.8	1

Table 2.3 Plastic-derived Fuels properties

Type of plastic	PET	HDPE	PVC	LDPE	PP	PS	Gasoline	Diesel
Density @ 15°C (g/cm ³)	0.9	0.89	0.84	0.78	0.86	0.85	0.78	0.807
Kinematic viscosity (mm ² /s)	-	5.08 @ 40°C	6.36 @ 30°C	5.56 @ 25°C	4.09 @ 40°C	1.4 @ 50°C	1.17	1.9 – 4.1
Flashpoint (°C)	-	48	40	41	30	26.1	42	52
Pour point (°C)	-	-5	-	-	-9	-67	-	6
Calorific value (MJ/kg)	28.2	40.5	21.1	39.5	40.8	43	42.5	42 – 46
Cetane number	56.54	n/a	n/a	n/a	42.23	n/a	n/a	54
Reference	(Çepelioğullar & Pütün, 2013; Kassargy <i>et al.</i> , 2018; M. Sarker <i>et al.</i> , 2011)	(Ahmad <i>et al.</i> , 2015)	(Çepelioğullar & Pütün, 2013; Manickaraja & Tamilkolundu, 2015)	(Satav <i>et al.</i> , 2020)	(Ahmad <i>et al.</i> , 2015)	(Blazsó, 2006; Kassargy <i>et al.</i> , 2018; Pinto <i>et al.</i> , 1999)	(Ahmad <i>et al.</i> , 2015)	(Ahmad <i>et al.</i> , 2015; Sekar <i>et al.</i> , 2021)

Tables 2.2 and 2.3 provide detailed information on the proximate analysis of various types of plastic-derived fuels and their properties, including the chemical composition and fuel characteristics of the end products. It can be concluded that from Table 2.2, HDPE, PP, and LDPE are the most promising plastics for energy production through pyrolysis due to their high calorific values between 37.4 – 49.4 MJ/kg, low moisture content (<0.4 wt%), minimal fixed carbon (<1.2 wt%), and high volatile content (94 – 99.8 wt%). PET and PVC can also be used in pyrolysis, but may yield slightly lower energy output (18 – 24.13 MJ/kg) compared to the others due to their lower calorific value and more complex residual composition. PS is also suitable for pyrolysis due to its high volatile content (<99 wt%) and decent calorific value (37.7–42.1 MJ/kg). However, PVC might be less efficient due to its relatively low calorific value (18 MJ/kg). From Table 2.3, PP and HDPE are the most promising candidates for pyrolysis or energy conversion, as they have high calorific values (39.5-40.8 MJ/kg) and relatively low viscosities, making them suitable for fuel production. PS has a high calorific value (43 MJ/kg) and could be an excellent energy source, but its low flashpoint and pour point suggest it may not be ideal for direct use in engines without treatment. PVC is less favorable due to its low calorific value (21.1 MJ/kg) and the potential challenges in handling its combustion products. Gasoline and diesel comparison with plastics shows that plastics like HDPE, LDPE, and PP have similar or even superior properties in some cases, while PVC and PET have lower energy potential.

2.4 Biodiesel Status in Malaysia

Biodiesel is a renewable and environmentally friendly alternative to traditional diesel fuel that has gained significant global attention due to its potential to reduce GHG emissions and reliance on fossil fuels. In Malaysia, biodiesel has been utilized in transportation since 2011, with the country leveraging its position as one of the largest palm oil producers to promote the use of palm oil-based biodiesel (Yusoff *et al.*, 2015; Zulqarnain *et al.*, 2020). The biodiesel initiatives have evolved over the years with several key programs aimed at increasing biodiesel use, enhancing environmental sustainability, and supporting the local palm oil industry. In 2015, Malaysia introduced the B7 biodiesel program, which mandated a 7% blend of palm oil-based biodiesel in

all diesel fuel sold in the country. This initiative aimed to reduce the carbon footprint by lowering GHGs and promoting the use of domestically produced biodiesel, thus supporting the palm oil sector (Mayandi & Suharjito, 2024; Solaymani, 2023; Umar *et al.*, 2018). By the end of 2015, the B7 program was fully enforced, marking a significant step toward integrating biodiesel into the national fuel supply. Building on the success of the B7 program, Malaysia launched the B10 biodiesel program in 2019, which increased the biodiesel blend to 10%. This program was designed to further reduce emissions and enhance the commitment to renewable energy, while also creating a more robust market for palm oil-based biodiesel (Zulqarnain *et al.*, 2020). The implementation of the B10 program reflects Malaysia's ongoing commitment to reducing its reliance on fossil fuels and mitigating climate change through the promotion of sustainable energy sources.

In 2019, Malaysia introduced the B20 biodiesel program, which mandates a 20% blend of palm oil-based biodiesel in all diesel vehicles. The B20 program aims to provide even greater environmental benefits by further reducing carbon emissions, improving air quality, and supporting the palm oil industry, which is a crucial sector of the Malaysian economy (Zulqarnain *et al.*, 2020). The B20 mandate is part of broader efforts to promote renewable energy use and contribute to achieving climate change targets under international agreements like the Paris Climate Accord. These biodiesel programs in Malaysia are significant not only for their environmental benefits but also for their economic impact. The increased use of palm oil-based biodiesel supports the agricultural sector, particularly the palm oil industry, which is a key contributor to Malaysia's economy. Moreover, biodiesel blends such as B7, B10, and B20 contribute to energy diversification efforts that reduce the dependency on fossil fuels and foster the development of sustainable energy solutions (Chung *et al.*, 2024; Suhara *et al.*, 2024). In conclusion, biodiesel programs in Malaysia, particularly the B7, B10, and B20 mandates, play a critical role in the efforts to reduce emissions, promote renewable energy, and bolster its palm oil industry. These programs serve as a model for other nations looking to transition to more sustainable fuel options and demonstrate the commitment to environmental stewardship and economic growth through domestically produced biodiesel.

The program followed several regulations to ensure the quality and safety of the biodiesel blend. These regulations included:

- MS 2008:2015 is the Malaysian standard for biodiesel, which specifies the requirements for biodiesel fuel, including its physical and chemical properties.
- MS 1595:2014 is the Malaysian standard for diesel fuel, which specifies the quality requirements for diesel fuel, including its physical and chemical properties.
- The Biofuel Act 2007 is the legislation that governs the production, sale, and use of biofuels in Malaysia. The Act mandates the use of biodiesel in transportation and sets standards for the production and distribution of biodiesel.
- The Biodiesel Industry (Standardization, Quality Control, and Monitoring) Regulations 2011: This regulation sets out the requirements for the quality control and monitoring of biodiesel production and distribution in Malaysia.

The B7 program in Malaysia, which was officially launched in December 2014 and fully implemented by November 2015, mandated that all diesel fuel sold in the country contain a minimum of 7% palm oil-based biodiesel. This initiative was part of the strategy to reduce its dependence on fossil fuels, promote renewable energy, and bolster the local palm oil industry. Initially, the program began with a 5% biodiesel blend in 2014, which gradually increased to 7% by 2015, ensuring a smooth transition for both consumers and fuel retailers (Lopes *et al.*, 2016; Yusoff *et al.*, 2015). Under the B7 program, fuel retailers were required to ensure that their facilities were compatible with biodiesel. This involved retrofitting infrastructure such as fuel pumps and storage tanks to handle the unique properties of biodiesel, which can be more corrosive than conventional diesel. To maintain fuel quality, the program required compliance with the Malaysian Standard MS 2008:2015 for biodiesel and MS 1595:2014 for diesel fuel. These standards set the physical and chemical properties that biodiesel must meet, ensuring that the fuel blend is suitable for use in all diesel engines and does not compromise vehicle performance (Umar *et al.*, 2018).

Building on the success of the B7 program, Malaysia introduced the B10 program in February 2019, which raised the biodiesel blend requirement to 10% for all diesel fuels sold nationwide. The B10 program followed a similar regulatory framework to the B7 program, maintaining strict compliance with the Biofuel Act 2007, Malaysian Standards, and the Biodiesel Industry (Standardization, Quality Control, and Monitoring) Regulations 2011. These regulations ensured that biodiesel was produced and distributed according to stringent quality control measures, thereby safeguarding both fuel quality and engine performance. Like the B7 program, the B10 initiative aimed to reduce GHG emissions, promote the use of renewable energy, and further support the local palm oil industry (Mostapha *et al.*, 2022; Recessary, 2023). Together, the B7 and B10 programs reflect Malaysia's commitment to sustainability by increasing the use of biodiesel in transportation. These programs not only support the renewable energy goals but also provide an important economic boost to the palm oil sector, making Malaysia a leading player in the global biodiesel market.

The use of biodiesel in the transportation sector presents both significant benefits and challenges. It offers several environmental advantages, including a reduction in GHGs and PM, making it a cleaner alternative to conventional diesel. By substituting fossil fuels, biodiesel contributes to a decrease in carbon emissions, which is crucial for mitigating climate change. Biodiesel production strengthens energy security in the country by reducing dependence on fossil fuels while supporting the local palm oil industry (Arumugam *et al.*, 2024; Suhara *et al.*, 2024). The implementation of the B7 and B10 biodiesel programs has been central to this transition, which promotes the use of biodiesel as a part of the broader strategy to embrace renewable energy sources and reduce GHGs from transportation (Sentanuhady *et al.*, 2022; Umar *et al.*, 2018). However, the widespread adoption of biodiesel also presents several challenges. A key disadvantage is the lower energy density of biodiesel compared to conventional diesel. On average, biodiesel contains around 10-12% less energy per liter than traditional diesel, which can result in reduced fuel efficiency and a higher frequency of refuelling for vehicles (Mohd Noor *et al.*, 2018; Yusoff *et al.*, 2021). This reduction in energy density can be a deterrent for consumers as it may lead to higher operational costs and less convenience. Additionally, the cost of biodiesel is often higher than that of conventional diesel,

primarily due to the higher costs associated with palm oil production and biodiesel processing. This price difference can make biodiesel less economically attractive to consumers, especially in a price-sensitive market (Mohammed *et al.*, 2023; Papilo *et al.*, 2022).

Another significant concern related to the use of biodiesel in Malaysia is the environmental impact of palm oil production, which serves as the primary feedstock for biodiesel. While biodiesel itself offers clear environmental benefits, the large-scale cultivation of palm oil has been linked to a range of environmental and social issues. Deforestation, habitat destruction, and loss of biodiversity are some of the major environmental consequences of expanding palm oil plantations (Dalheimer *et al.*, 2024; Hanafiah *et al.*, 2021). The conversion of forests to palm oil plantations has resulted in the loss of critical habitats for endangered species and has contributed to soil erosion, water pollution, and carbon emissions from land-use changes. Moreover, the palm oil industry has faced criticism for its role in human rights violations, including disputes over land ownership and poor labour conditions on plantations (Ayompe *et al.*, 2021; Vijay *et al.*, 2016). These challenges have led to calls for more sustainable practices in palm oil production, such as those promoted by the Roundtable on Sustainable Palm Oil (RSPO), which aims to ensure that palm oil is produced in an environmentally and socially responsible manner. In conclusion, while biodiesel offers clear environmental and economic benefits for Malaysia, its implementation in transportation is not without challenges. Issues related to fuel efficiency, cost, and the environmental impact of palm oil production need to be addressed to ensure the sustainability of biodiesel as a long-term alternative to fossil fuels. As Malaysia continues to expand its biodiesel programs, efforts to mitigate these challenges, such as improving production processes and promoting sustainable palm oil practices, are essential for ensuring the continued success of biodiesel in the energy transition.

2.5 Biodiesel Fuel Productions and Characteristics

Biodiesel is a renewable fuel primarily produced through the transesterification process, which involves reacting vegetable oils, animal fats, or waste oils with alcohol,

usually methanol or ethanol, in the presence of a catalyst like NaOH or KOH. This reaction yields fatty acid methyl esters (FAME), the key component of biodiesel, along with glycerol as a byproduct (Ghiasi *et al.*, 2022; Liu & Tao, 2022; Palani *et al.*, 2022; Hoang *et al.*, 2021; Zhong *et al.*, 2023). The production of biodiesel from palm oil follows the same basic transesterification process, though there are unique aspects of palm oil that influence the process. Palm oil is derived from the fruit of the oil palm tree and can be obtained either by mechanical pressing or using solvent extraction methods. The crude palm oil (CPO) produced in this way typically contains various impurities, including free fatty acids (FFA), water, sterols, phospholipids, and odorants, all of which can impact the efficiency of the transesterification process and the quality of the resulting biodiesel (Arumugam *et al.*, 2024; Faraguna *et al.*, 2019; Shaikh & Shaikh, 2021). The presence of FFA is challenging because they do not react easily during the standard transesterification process, which typically involves triglycerides, the primary components of fats and oils. As a result, when using palm oil with high FFA, a two-step process is often employed. In the first step, FFA is esterified before the conventional transesterification process is applied (Ulakpa *et al.*, 2022).

The transesterification itself involves the chemical breakdown of triglycerides into biodiesel (methyl esters) and glycerol. This reaction takes place when triglycerides are mixed with methanol or ethanol in the presence of a catalyst such as NaOH or KOH. The alcohol used helps in breaking the triglycerides into smaller molecules, creating biodiesel that can be used as an alternative to conventional diesel fuel. While the catalyst accelerates the reaction, it is the alcohol that plays a key role in forming the esters needed for biodiesel production (Pandit *et al.*, 2023). Although the process is similar for most oils, palm oil presents specific challenges due to its high saturated fat content. This can impact the cold flow properties and stability of the biodiesel, affecting its performance, especially in cooler climates. Additionally, the refining of palm oil to remove contaminants such as water and phospholipids is crucial to ensure a smooth and efficient transesterification process. These characteristics must be carefully managed to ensure that the biodiesel produced meets the necessary standards for use in vehicles and other machinery (Zulqarnain *et al.*, 2020). While the production of biodiesel from palm oil follows the general process of transesterification, the unique

characteristics of palm oil, such as its high saturated fat content and presence of impurities, require additional refining steps and careful management during the biodiesel production process. This ensures that high-quality biodiesel is produced efficiently and effectively. Figure 2.2 illustrates the transesterification process of palm oil, providing a visual representation of the steps involved in transforming crude palm oil into biodiesel.

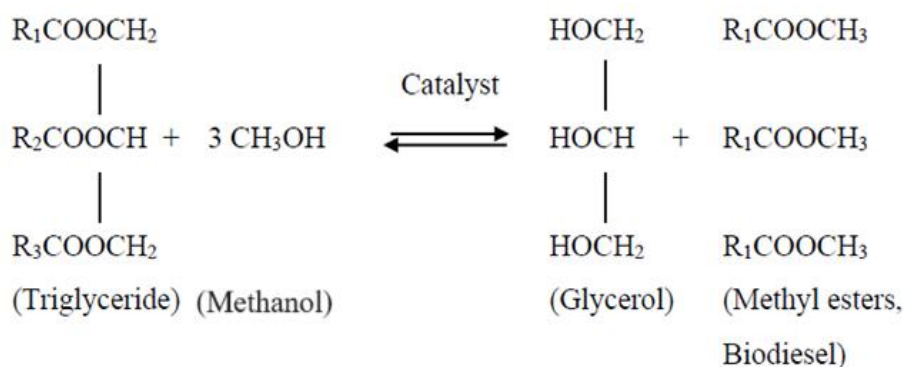


Figure 2.2 Transesterification process of raw palm oil

The production of biodiesel primarily involves the transesterification process, which converts triglycerides into simpler alkyl esters known as biodiesel. This process effectively reduces the viscosity of oils and makes them suitable for use as an alternative to conventional diesel in engines. Methyl esters were produced by reacting vegetable oils or animal fats with methanol, which is the most used form of biodiesel due to their lower cost and favourable properties, such as lower viscosity compared to the original oils. This reduction in viscosity is crucial as it improves fuel atomization in the combustion chamber, leading to better AF mixing, enhanced combustion efficiency, and reduced emissions (Mohammed *et al.*, 2023; Pandit *et al.*, 2023; Yesilyurt & Cesur, 2022). NaOH is commonly used as a catalyst in the transesterification process primarily due to its cost-effectiveness and speed. This catalyst facilitates the conversion of triglycerides into FAME, the key component of biodiesel. The use of NaOH is particularly efficient for oils with low FFA content, such as palm oil, resulting in faster reactions and higher yields (Pandit *et al.*, 2023). As a result, NaOH remains one of the most widely used catalysts in biodiesel production.

Once biodiesel is produced, it can be blended with petroleum diesel using different methods. The two most common blending techniques are splashing blending and manifold blending. The splash blending method involves adding a predetermined volume of pure biodiesel to a storage tank, followed by the addition of petroleum diesel. The two fuels naturally mix over time. While this method is straightforward and inexpensive, it may not produce a completely uniform mixture, leading to some variability in fuel quality (Maharjan *et al.*, 2022). In contrast, manifold blending is a more controlled and precise process. It involves the simultaneous addition of biodiesel and petroleum diesel to the tank with the use of meters and valves to regulate the flow of both fuels. This method ensures that the desired blend ratio is consistently achieved and results in a more uniform and higher-quality blend. Manifold blending is particularly advantageous for large-scale biodiesel production where maintaining fuel consistency is crucial (Brahma *et al.*, 2022; Wang *et al.*, 2017). The production of palm oil biodiesel follows these processes, incorporating both transesterification and blending methods to ensure high-quality fuel. Figure 2.3 illustrates the various steps involved in palm oil biodiesel production, highlighting the importance of blending techniques and quality control measures to produce biodiesel that meets the necessary standards for use in diesel engines. In conclusion, biodiesel production from palm oil involves several key steps, including transesterification and careful blending of biodiesel with petroleum diesel. The use of methanol and NaOH in the transesterification process, along with controlled blending methods, ensures the production of high-quality biodiesel that can serve as a sustainable and renewable alternative to conventional diesel fuel. These processes contribute to the overall development of renewable energy sources, supporting both environmental goals and the growth of local industries.

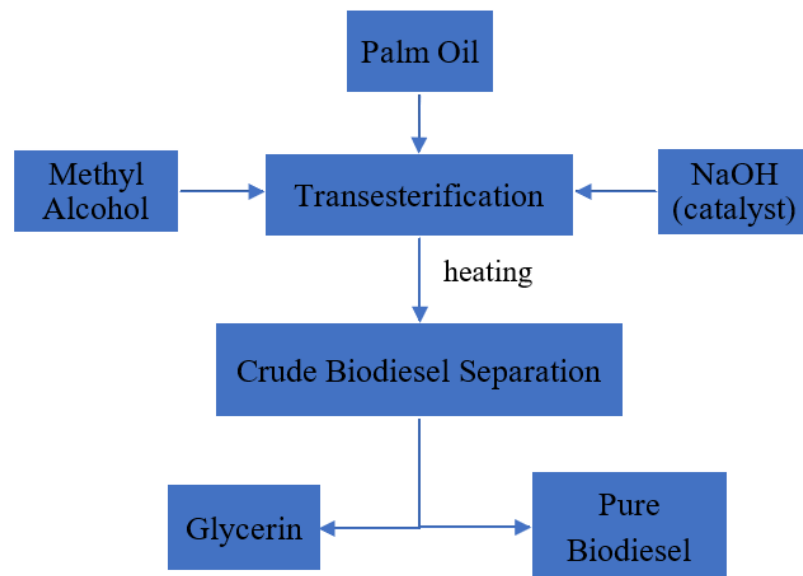


Figure 2.3 Steps of the palm oil biodiesel manufacturing process

Biodiesel is increasingly recognized for its ability to reduce harmful emissions when compared to conventional diesel fuel. According to Abed *et al.* (2019), biodiesel blends have been shown to significantly decrease CO, HC, CO₂, and smoke emissions, making them a promising alternative for cleaner energy. The oxygen content in biodiesel facilitates more complete combustion, leading to fewer unburned hydrocarbons and particulate emissions, which contribute to improved air quality. Further supporting this, Senthilkumar *et al.* (2015) examined the effects of biodiesel blends derived from various palm oil mixtures and found that these blends reduced unburned HC emissions by 73% and CO emissions by 46% when compared to conventional diesel. These reductions are particularly important because HC and CO are major contributors to air pollution and have harmful health effects, including respiratory problems and cardiovascular diseases. Raju *et al.* (2020) also explored the potential of biodiesel made from waste tamarind and found significant reductions in multiple emissions, including CO (10.68%), HC (33.33%), NO_x (10.33%), and smoke (27.72%). These results highlight the environmental benefits of using biodiesel from waste feedstocks, as it reduces the impact of fossil fuel consumption while supporting waste management efforts.

The compatibility of biodiesel with diesel engines is another key advantage. Biodiesel shares several important characteristics with conventional diesel fuel, including energy content, viscosity, and lubricity, which makes it suitable as a direct replacement for diesel fuel in most diesel engines. Liu and Tao (2022), Man *et al.* (2016), and Ramesh *et al.* (2022) reported that biodiesel provides similar power output and fuel efficiency to conventional diesel. This is particularly beneficial for consumers and industries looking to transition to more sustainable fuel options without sacrificing vehicle performance. Furthermore, high lubricity in biodiesel reduces engine wear, which can extend the lifespan of engine components and improve overall engine longevity (Jiang *et al.*, 2024; Sriprathum *et al.*, 2023). Biodiesel does have a slightly higher viscosity than diesel fuel, but this can be adjusted through blending, ensuring proper atomization and combustion. These characteristics make biodiesel a "drop-in" fuel, meaning it can be used in diesel engines with little to no modification, making it an attractive alternative for reducing reliance on fossil fuels while maintaining engine performance.

Biodiesel offers several advantages over conventional diesel fuel, including its impact on engine performance and environmental benefits. According to Malla *et al.* (2024), biodiesel has an energy content of approximately 118,300 BTU per gallon, which is about 90% of the energy content of traditional diesel (130,000 BTU per gallon). While it provides slightly less energy than diesel, biodiesel remains a viable alternative fuel for transportation, especially in terms of sustainability and reducing reliance on fossil fuels. One of the key benefits of biodiesel is its superior lubricity compared to conventional diesel fuel. Lubricity refers to the ability of fuel to reduce friction between moving parts in an engine, helping to reduce wear and extend the lifespan of fuel system components. Studies by Jiang *et al.* (2024) and Pumpuang *et al.* (2024) indicated that biodiesel can increase lubricity by up to 27% compared to diesel, which significantly helps protect the internal parts of the engine, such as injectors and fuel pumps. This increased lubricity is especially beneficial in preventing corrosion and reducing maintenance costs over time. In addition to its lubricity, viscosity in biodiesel is comparable to that of diesel fuel, allowing it to flow easily through fuel lines, filters, and injectors without causing clogs. The US EPA agency has noted that while the viscosity of biodiesel is slightly higher than diesel, it still falls

within the acceptable range for diesel engines (Maheshwari *et al.*, 2022). This ensures that biodiesel can be used as a drop-in replacement for diesel without the need for significant engine modifications.

The use of higher biodiesel blends, particularly those derived from palm oil, can introduce challenges related to increased viscosity, poor cold flow properties, and lower volatility. These issues can cause significant operational difficulties in diesel engines, including engine deposits, injector coking, and piston ring sticking, which can negatively affect engine performance and longevity. Guo *et al.* (2016) found that at a blend ratio of 20% palm oil biodiesel (B20) and 80% petroleum diesel, the kinematic viscosity of the fuel increased by approximately 10% compared to petroleum diesel alone. This increase in viscosity can affect the fuel's ability to flow smoothly through the fuel system, potentially leading to clogged fuel filters and inefficient fuel atomization, particularly in older engines that were not originally designed to run on biodiesel blends. The problem becomes more pronounced with higher biodiesel concentrations. For instance, at blend ratios of 50% palm oil biodiesel (B50) and 100% palm oil biodiesel (B100), the kinematic viscosity increased by approximately 25% and 45%, respectively. These substantial increases can lead to challenges such as reduced fuel efficiency, difficulty in starting engines, and the accumulation of carbon deposits in the combustion chamber, which further impairs engine power and efficiency. To address these issues, it is crucial to carefully select the appropriate biodiesel blend ratio for each application and engine type. Using high-quality biodiesel with low viscosity can reduce the likelihood of operational problems. Incorporating fuel heaters can improve fuel flow, particularly in colder environments where biodiesel is more prone to gelling and thickening. Studies by Hamdi *et al.* (2023), Milano *et al.* (2022), and Veza *et al.* (2022) suggested these measures can help mitigate the effects of increased viscosity, ensuring smoother engine operation and enhancing the performance of biodiesel-powered engines. While biodiesel offers environmental benefits such as reduced emissions, careful attention must be paid to its physical properties, especially at higher blend ratios, to avoid engine performance issues.

2.6 Overview of Engine Performance and Emissions for Plastic-derived Diesel Fuels

While biodiesel fuels such as palm oil methyl esters have been widely explored for their renewable properties and compatibility with diesel engines, emerging interest has turned toward alternative sources like plastic-derived diesel fuels. Understanding how these fuels behave in terms of engine performance and emissions is essential, especially as they present unique combustion characteristics compared to conventional biodiesel. This section synthesizes findings from various studies to present a comparison of engine performance and emissions associated with plastic-derived diesel fuels. The performance and emissions characteristics of plastic-derived diesel fuels have been widely studied in different engine types and under various operating conditions. Key performance indicators such as brake thermal efficiency (BTE) and brake-specific fuel consumption (BSFC) have been used to evaluate the energy efficiency and fuel economy of these fuels. Emission profiles including CO, CO₂, HC, and NO_x have been analyzed to assess their environmental impact. While plastic-derived diesel fuels demonstrate potential benefits, challenges such as higher viscosity, reduced volatility, and elevated NO_x emissions in some blends have been noted. These issues highlight the need for optimized fuel properties and engine tuning to ensure compatibility and performance.

Table 2.4: Trends of engine performance and emissions associated with plastic-derived diesel fuels at various operating conditions

Engine type	Plastic type (volume/ratio)	Engine performance			Emissions			Ref
		BTE	BSFC	CO	CO ₂	HC	NO _x	
4 stroke, 1-cylinder, air-cooled, naturally aspirated, 6.4 kW @ 3600 rpm, (50% load)	HDPE (100%)	↓	↑	↑	-	↑	↑	Pumpuang <i>et al.</i> , 2024
	PP (100%)	↑	↓	↓	-	↑	↓	
4 stroke, 1-cylinder, water-cooled, naturally aspirated, 3.5 kW @ 1500 rpm, (100% load, 240 bar, CR = 18:1)	HDPE (100%)	-	-	↓	-	↑	↓	Modi & Patel, 2023
	PP (100%)	-	-	↓	-	↑	↓	
4 stroke, 1-cylinder, air-cooled, naturally aspirated, 4.4 kW @ 3600 rpm, (3000 rpm)	HDPE (10%)	↓	↑	↓	↓	↓	↓	Yaqoob <i>et al.</i> , 2024
4 stroke, 1-cylinder, water-cooled, naturally aspirated, 12.1 kW @ 2200 rpm	Diesel/Ethanol (85/15%) with carbon nano additive	↓	↑	↑	↓	↑	↑	(Li <i>et al.</i> , 2025)
4 stroke, 1-cylinder, naturally aspirated, 5.2 kW @ 1500 rpm, (PPO 10%, 10 kg load)	HDPE (58.6% from mixed)	↓	↑	↑	↑	↑	↑	Singh <i>et al.</i> , 2020
4 stroke, 1-cylinder, water cooling, turbocharged, 12 kW @ 2000 rpm, (operating condition are indicated)	PP (20%)	-	-	↑	-	↑	↑	Januszewicz <i>et al.</i> , 2023

mean effective pressure = 2.8 bar, intake absolute pressure = 0.98 bar)

4 stroke, 1-cylinder, water cooling, naturally aspirated, 5.2 kW @ 1500 rpm, (100% load)	PP (20%)	↑	↓	↓	-	↑	↑	Mehanathan <i>et al.</i> , 2025
4 stroke, 6-cylinder, water cooling, naturally aspirated, 164 kW @ 2500 rpm, (50% load, 1500 rpm, injection pressure 138 MPa)	HDPE (20%)	-	-	↓	-	↓	↓	Yusuf <i>et al.</i> , 2024
4 stroke, 1-cylinder, air-cooled, naturally aspirated, 3.5 kW @ 3600 rpm, (2100 rpm)	PP (10%)	↓	↑	↑	↑	-	↑	Ilmi <i>et al.</i> , 2024
4 stroke, 6-cylinder, water cooling, naturally aspirated, 164 kW @ 2500 rpm, (75% load, 1600 rpm, injection pressure 150 MPa, distilled water as washing solution)	HDPE (15%)	-	-	↓	-	↑	↑	Yusuf <i>et al.</i> , 2023
4 stroke, 4-cylinder, liquid-cooled, naturally aspirated, 50.7 kW @ 2600 rpm, (100% load, 1500 rpm, 10% PPO)	Mixed of PP, PS, and HDPE	↓	↑	↓	↓	↓	↓	Mustayen <i>et al.</i> , 2023

Table 2.4 shows the trends of engine performance and emissions from current studies, mostly from HDPE and PP additives. In general, the comparative analysis of studies on plastic-derived fuels highlights their potential as feasible alternatives to conventional diesel, particularly in blended forms. These, derived from HDPE and PP plastics, have shown potential in reducing reliance on conventional fossil fuels. Their suitability for the pyrolysis process and availability make them the main purpose of this research. The extent of adaptation required for effective use varies significantly depending on engine type, operating conditions, and blended ratios. Previous research indicated that plastic-derived diesel fuels could achieve comparable or slightly lower BTE and high BSFC relative to diesel, emphasizing the need for blend optimization and engine tuning. Emissions profiles further demonstrated their potential environmental benefits, with a reduction of CO and HC emissions observed in most cases. However, higher NO_x emissions remain a consistent challenge attributed to elevated combustion temperatures associated with these fuels. Despite the progress, the review underscores key gaps in existing research. Limited data availability for critical parameters such as BTE, BSFC, and CO₂ emissions across diverse engine types and operational conditions delays the establishment of performance benchmarks. Addressing challenges such as high viscosity, emissions control, and combustion quality is essential to enhance the applicability of plastic-derived fuels. Comprehensive testing across various engine types, load conditions, and environmental settings is necessary to develop standardized guidelines and optimize these fuels for broader adoption. By addressing these gaps, plastic-derived diesel fuels could play an essential role in promoting sustainable energy solutions while mitigating plastic waste challenges.

2.7 Engine Emissions and Their Formation

Exhaust gas, also known as flue gas, is a byproduct of fuel combustion in engines and energy systems encompassing fuels like natural gas, gasoline, and diesel. Depending on the engine type, exhaust gases are discharged into the atmosphere through exhaust pipes, flue gas stacks, or propelling nozzles (Čampara *et al.*, 2018). The characteristics of exhaust emissions are significantly influenced by driving conditions and operating parameters, making these factors key determinants in

understanding emission behaviours. Research on heavy-duty diesel vehicles in real-world scenarios has demonstrated that operating conditions have a substantial impact on emission profiles. Elemental carbon emissions tend to increase during cruising modes while organic carbon emissions are more pronounced during idling modes (Deng *et al.*, 2020; He *et al.*, 2024; Tham *et al.*, 2023). These findings highlight the variability in exhaust emissions based on vehicle activity, engine load, and combustion dynamics. Despite these insights, inconsistencies in emission data across different operating conditions limit the comprehensive understanding of how various factors influence exhaust emissions. The gaps in systematic reporting and analysis hinder the development of strategies to optimize engine performance and reduce environmental impact.

Exhaust emissions from diesel engines are influenced by various factors, particularly engine load, with significant differences observed between idling and cruise modes. Research by Duan *et al.* (2023), Kim and Choi (2020), and Liang *et al.* (2024) highlighted that VOC emissions decrease rapidly as the engine load increases, suggesting that the emission profiles can vary significantly depending on the operational conditions of the engine. These variations underscore the importance of further research to understand how different operating conditions affect the formation of exhaust emissions. The combustion process in diesel engines involves the conversion of chemical energy from the fuel into mechanical energy, while also producing heat and exhaust emissions (Hazar & Özmen, 2022; Latache, 2021). To achieve this, key inputs such as air, fuel, and lubricant are essential for driving the internal combustion process, which powers vehicles, trucks, locomotives, and marine vessels. Figure 2.4 illustrates the basic inputs and the products produced during the combustion process, highlighting the interconnected nature of fuel, air, and mechanical output. The engine process involves the combustion of air, fuel, and lubricant, which contribute specific elements to the exhaust emissions. Air consists of 21% oxygen and 79% nitrogen, supplied at 8.5 kg/kWh. Fuel is primarily composed of HC (97%) and sulphur (3%), supplied at 175 g/kWh, while lubricant contains HC (97%), carbon (2.5%), and sulphur (0.5%), with a consumption rate of 1 g/kWh. During combustion, the engine produces heat, mechanical work, and exhaust gases, which include O₂

(13%), NO_x at 1500 ppm, CO₂ at 5.6%, water vapor (H₂O) at 5.35%, CO at 60 ppm, HC at 180 ppm, SO_x at 600 ppm, and nitrogen particulates at 120 mg/m³.

The AF ratio is a critical factor in determining the composition of exhaust gases. As shown in Figure 2.5, when the fuel mixture is fuel-rich, there is less air than needed for complete combustion, and higher levels of HC and CO are produced (Leman *et al.*, 2017). In contrast, a lean-rich mixture typically seen during engine start-up leads to lower CO emissions, but higher NO_x emissions as excess oxygen encourages the formation of NO_x (Hosseini & Butler, 2019; Shadidi *et al.*, 2021). Studies by Ding *et al.* (2022) and Morón *et al.* (2021) have also confirmed that an abundance of oxygen during the combustion process tends to increase NO_x emissions due to the higher temperatures generated by the surplus oxygen. These findings highlight the complex interplay between engine load, AF mixture, and exhaust emissions. Further research is needed to optimize engine performance and reduce harmful emissions by adjusting operating parameters like load and AF ratios. The next subsection discusses each emission formation accordingly.

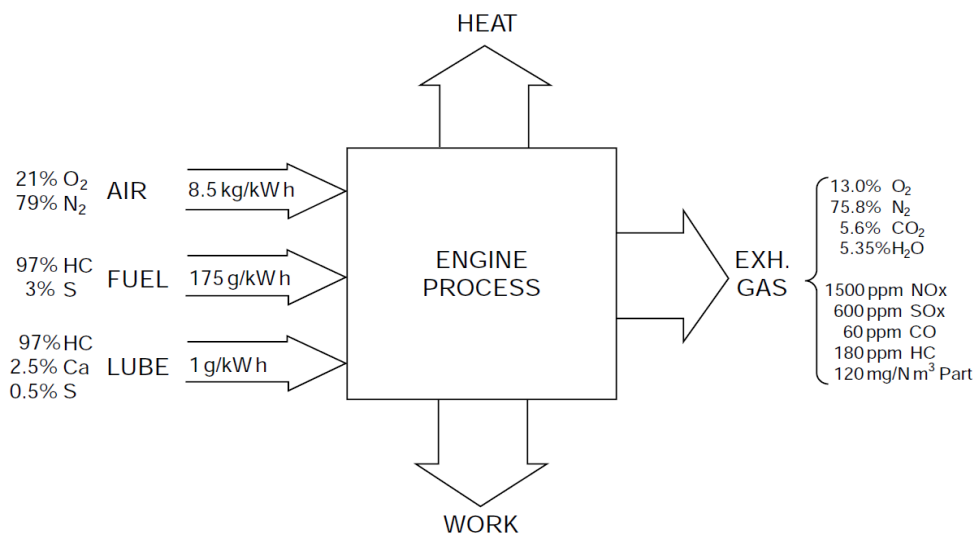


Figure 2.4 Common classification of input and output of a low-speed diesel engine (Hazar & Özmen, 2022; Latarche, 2021)

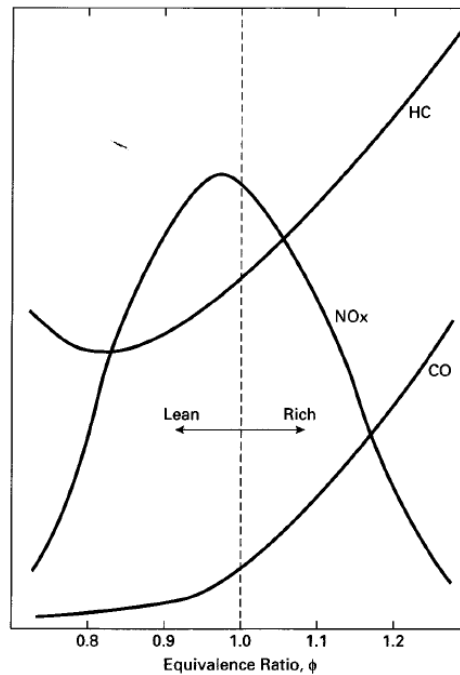


Figure 2.5 Emissions emitted as AF equivalence ratio (Leman *et al.*, 2017)

2.7.1 Formation of CO and CO₂

CO emissions are primarily a result of incomplete combustion, influenced by the availability of oxygen during the process. As depicted in Figure 2.5, CO emissions are higher in fuel-rich mixtures compared to fuel-lean mixtures. This occurs because insufficient oxygen in fuel-rich mixtures prevents the complete oxidation of carbon in the fuel to CO₂, leading to the formation of CO instead (Ghany *et al.*, 2024a; Scribano *et al.*, 2021). High temperatures within the combustion chamber can cause the dissociation of CO₂ into CO and O₂, further increasing CO emissions. The process of CO formation and its subsequent oxidation to CO₂ is a crucial pathway in the combustion of HC. Hydrocarbon fuels initially decompose into CO, which is then oxidized to CO₂. In diesel engines, which predominantly operate under fuel-lean conditions, CO emissions are typically low due to the excess oxygen available for oxidation. Shi *et al.* (2022) observed that most of the heat released during the combustion process stems from the oxidation of CO-to-CO₂, underscoring the importance of this reaction in energy release during combustion. This relationship is expressed in Equation 2.1, which outlines the chemical pathway for CO oxidation.



The level of CO emissions produced during combustion is significantly influenced by the AF equivalence ratio. At stoichiometric conditions where the AF ratio is perfectly balanced for complete combustion, CO emissions exhibit a non-linear behaviour due to the dynamic chemical reactions within the combustion chamber (Yang *et al.*, 2021). In multi-cylinder engines, discrepancies in combustion dynamics can occur. Some cylinders may operate in a fuel-lean mode (excess oxygen), while others run in a fuel-rich mode (insufficient oxygen). This imbalance results in a higher average equivalence ratio, leading to increased CO emissions beyond the expected values (Dey *et al.*, 2021; Scribano *et al.*, 2021). During the combustion and expansion phases, the carbon-oxygen-hydrogen (C-O-H) chemical system remains in a near-equilibrium state until the freezing point of NO formation is reached. At this stage, the CO concentration stabilizes, influenced by both the combustion environment and the rate of cooling in the exhaust system. Regardless of whether the engine operates in a fuel-lean or fuel-rich mode, the concentration of CO in the exhaust gas can be estimated using equilibrium chemistry principles. It is important to note that the CO levels measured in the exhaust are typically lower than the peak levels formed in the combustion chamber but higher than the equilibrium concentrations of the exhaust gas after cooling. This discrepancy arises due to the chemical kinetics of the C-O-H system, which involves key reactions such as the following three-body recombination reactions, as shown in Equations 2.2 to 2.4. These reactions highlight the importance of controlling the reaction rates to optimize the conversion of CO-to-CO₂ and minimize CO emissions.



Minimizing the time an engine operates in fuel-rich conditions, such as during start-up or acceleration, is critical for reducing CO emissions (Brahma *et al.*, 2022;

Hamzah *et al.*, 2022; Iavarone & Parente, 2020). Diesel engines, which typically operate in fuel-lean conditions, inherently produce lower levels of CO compared to gasoline engines. The excess oxygen in lean conditions promotes the complete oxidation of CO-to-CO₂, thereby improving combustion efficiency and reducing emissions. Advancements in engine design, such as precise fuel injection systems and enhanced AF mixing techniques, further contribute to the reduction of CO emissions. These improvements are crucial for achieving regulatory compliance and enhancing the environmental performance of diesel engines.

2.7.2 Formation of HC

HC emissions result from unburned or partially burned fuel released during the exhaust phase of engine operation. These emissions are particularly pronounced during engine start-up and warm-up phases when fuel is undergoing vaporization and oxidation. Factors like low combustion chamber temperatures and incomplete AF mixing contribute to these elevated emissions during these conditions (Chen *et al.*, 2022; Yilmaz & Atmanli, 2017). For regulatory and monitoring purposes, HC emissions are categorized into total hydrocarbons (THC) and non-methane organic gases (NMOG). While methane (CH₄) is classified as a GHG, it is considered less photochemically reactive than other hydrocarbons and is often treated as a separate entity. HC concentrations are typically expressed in parts per million (ppm) of carbon atoms in exhaust emissions. HC emissions from diesel engines are highly diverse, comprising up to 4,444 distinct HC compounds with approximately 1,020 classified as major compounds and 100–200 as minor compounds (Leman *et al.*, 2017). These compounds include both unaltered parent fuel hydrocarbons that survive combustion and secondary hydrocarbons that result from incomplete chemical reactions during the combustion process. About 50% of HC emissions are secondary hydrocarbons. These include compounds like acetaldehyde, formaldehyde, 1,3-butadiene, and benzene, which are products of partial reactions in the combustion process. These compounds are of particular concern due to their classification as toxic pollutants by the US EPA because of their potential carcinogenic and health-damaging properties (Ghadikolaie *et al.*, 2019; Yilmaz & Atmanli, 2017).

The level of HC emissions in diesel engines depends on several factors. Lower temperatures during start-up and idling result in incomplete combustion and inadequate AF mixing, leading to localized fuel-rich zones where combustion is incomplete, and conditions like low engine load or cold start exacerbate HC formation (Hao *et al.*, 2021; Nyongesa *et al.*, 2024; Wang *et al.*, 2024). Efforts to reduce HC emissions include advancements in combustion optimization by improving AF mixing and combustion efficiency to minimize unburned hydrocarbons using after-treatment technologies such as catalytic converters and diesel oxidation catalysts to oxidize HC into less harmful compounds like CO₂ and water, and reformulation of fuels to reduce the aromatic content (Sunoko *et al.*, 2023; Ye & Peng, 2023). Table 2.5 shows the potential sources of HC emissions from diesel engines. Gaps between piston rings and cylinder walls trap fuel-air mixtures (Cheng, 2024). These areas are cooler than the combustion chamber, preventing complete combustion and causing unburned hydrocarbons to be released, making crevices contribute to 38%. HC can dissolve into the oil on the cylinder walls and is released when the oil heats up during combustion, contributing to HC emissions from oil layers by 16% (Kushwaha & Saraswati, 2016). Fuel hydrocarbons can stick to engine surfaces like the combustion chamber walls and piston crowns. These deposits release unburned hydrocarbons when combustion is incomplete, contributing to 16% of the source of HC emissions. If the fuel does not vaporize properly before combustion, it cannot burn fully, leading to unburned HC formation (Malfi *et al.*, 2021). This is more noticeable during cold starts or low-temperature operations, making liquid fuels themselves contribute to 20% of HC emissions. Last, flame quenching happens when the flame goes out near the engine walls due to lower temperatures, preventing complete combustion, and unburned hydrocarbons can leak through the exhaust valve during the exhaust stroke, contributing 5% for each source (Bellis *et al.*, 2024).

Table 2.5 Sources of estimated HC emissions in an engine (Tondelli *et al.*, 2000)

Sources	HC emissions (%)
Crevices	38
Oil layers	16
Deposits	16
Liquid fuel	20
Flame quench	5
Exhaust valve leakage	5
Total	100

Diesel fuel has a higher boiling point and greater molecular weight compared to gasoline, which affects its combustion characteristics. This leads to incomplete combustion of some fuel components, causing them to partially oxidize and form unburned HC that contributes to exhaust emissions. These hydrocarbons are typically heavier in molecular weight compared to those from gasoline combustion, leading to a broader range of HC compounds in the exhaust (Ghodke *et al.*, 2022; Reşitoğlu *et al.*, 2015). The measurement of HC emissions is often conducted using a flame ionization detector (FID) at temperatures around 190°C. This method captures a wide spectrum of hydrocarbons, from light compounds like methane to heavier hydrocarbons in the vapor phase. The heavier hydrocarbons condense as they travel through the exhaust system, where they are filtered out along with PM before reaching the detector (Apicella *et al.*, 2024; Dumitrescu *et al.*, 2018; Thirumalini & Malemutt, 2021). PM emissions are measured similarly, beginning with the filtration of diluted exhaust gases at temperatures below 52°C. This process indirectly measures a portion of the total HC emissions. Soot particles in the exhaust can absorb condensed HC gases, and when extracted using a solvent, the soot contributes about 15-45% to the total particulate mass (Ball *et al.*, 2020; Gordon *et al.*, 2014; Manisalidis *et al.*, 2020). This highlights the intertwined nature of HC and PM emissions in diesel engines, emphasizing the importance of considering both in efforts to reduce overall emissions. The extent of unburned fuel emissions is heavily influenced by the AF ratio and the combustion process. Under fuel-lean mixture conditions, some of the fuel may combust during the primary combustion phase, but in fuel-rich mixtures, the combustion is incomplete. In

these conditions, fuel continues to oxidize slowly in the expansion phase, leading to unburned hydrocarbons being released into the exhaust (Chanphavong & Zainal, 2019; Jung *et al.*, 2012; Xiang *et al.*, 2020; Zhang *et al.*, 2021). The incomplete mixing of fuel with air and the quenching of oxidation reactions result in HC emissions, emphasizing the need for optimized combustion parameters such as the AF mixture and ignition timing to reduce these emissions.

2.7.3 Formation of NO_x

The formation of NO_x in diesel engines occurs when N₂ and O₂ molecules in the combustion chamber break apart due to the high temperatures during combustion. This thermal dissociation leads to the formation of reactive nitrogen and oxygen atoms, which then combine to produce NO and NO₂ emissions (Chen *et al.*, 2021; Radwan & Paul, 2024; Wu *et al.*, 2020). Several engine operating parameters, including the AF equivalence ratio, ignition timing, engine speed, and manifold pressure, have been shown to significantly influence NO_x concentrations in the exhaust. Studies indicate that these factors can alter the conditions under which NO_x is formed, with some parameters, such as engine load, that are more closely linked to NO_x emissions (Lv *et al.*, 2019; Mohd Noor *et al.*, 2018; Ogunkunle & Ahmed, 2021). The formation of NO_x is highly temperature-dependent. During engine start-up and warm-up, NO_x emissions tend to be relatively low but increase as engine load rises, causing the combustion chamber temperature to climb. The increased temperature accelerates the chemical reactions that produce NO and NO₂. Additionally, compression ignition engines tend to produce higher concentrations of NO₂ compared to spark ignition engines, with NO₂ comprising 10-30% of the total NO_x emissions. In the atmosphere, NO reacts with unburned HC in the presence of sunlight, leading to the formation of smog, which contributes to poor air quality, especially in urban areas (Mariani *et al.*, 2021; Xiang *et al.*, 2020; P. Zhang *et al.*, 2021).

The formation of NO_x in combustion engines is primarily driven by the thermal or Zeldovich mechanism, which involves three key chemical reactions. This mechanism plays a crucial role in the formation of NO at high temperatures,

particularly at the flame front during combustion. Although the flame front is relatively small compared to the larger volume of hot gases in the combustion chamber, the amount of NO formed through the Zeldovich mechanism remains comparatively modest when contrasted with other mechanisms, such as those involving thermal hydrogen cyanide and ammonia. These other mechanisms produce NO through reactions with oxygen (O) and hydroxyl (OH) radicals (Mariani *et al.*, 2021; Mohammadi & Neshat, 2020; Zengel *et al.*, 2020). The extended Zeldovich mechanism, as represented by Equations 2.5 to 2.7, highlights the key reactions that generate NO under high-temperature combustion conditions. Lavoie's modification in Equation 2.8 suggests that these reactions may approach a partial equilibrium, which is essential for understanding the dynamics of NO formation under various operational conditions. The Fenimore mechanism, which occurs under rich combustion conditions, accelerates NO formation. This process is initiated by HC radicals interacting with molecular nitrogen, resulting in the formation of intermediate compounds such as hydrogen cyanide (HCN), which then react to produce NO at lower concentrations (Lee *et al.*, 2021; Yun *et al.*, 2021). In addition, the formation of NO_x involves the reversible conversion of NO to NO₂, as shown in Equations 2.10 and 2.11, where NO reacts with O and H to form NO₂. These complex reactions depend on various factors, including combustion temperature, fuel composition, and the presence of other chemical species. A simplified graphical overview of NO_x formation mechanisms is provided in Figure 2.6, offering a clearer understanding of how NO_x is generated in different combustion environments.



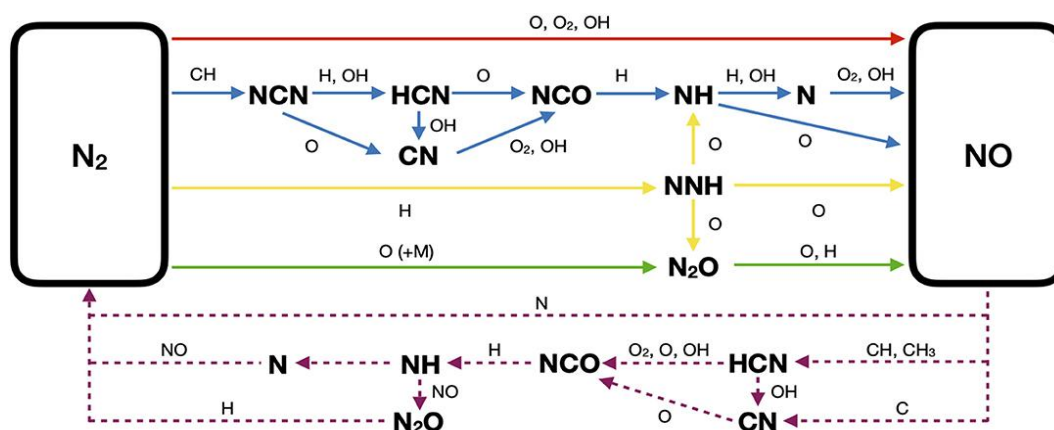


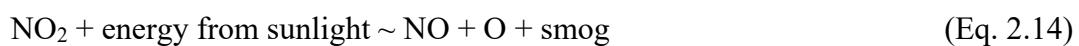
Figure 2.6 Simplified the complex structure of NO_x formation pathways from NO and N₂ species (Iavarone & Parente, 2020)

At low temperatures, N₂ in the atmosphere remains stable as a diatomic molecule and does not readily react. However, when exposed to high temperatures inside a combustion chamber, typically ranging from 2500–3000 K, nitrogen molecules dissociate into reactive monoatomic nitrogen (N), as shown in Equation 2.7 (Balandina *et al.*, 2020; Iavarone & Parente, 2020; Slavchov *et al.*, 2020). This high temperature is crucial for driving the formation of NO_x as the reactive nitrogen atoms can easily combine with oxygen to form NO, a major component of NO_x emissions. In addition to N, other gases such as O₂ and water vapor (H₂O) also contribute to NO_x formation at elevated temperatures. Oxygen molecules dissociate into atomic O, which reacts with nitrogen to form NO, while water vapor can break down into OH radicals, which further facilitate the creation of NO and NO₂. These reactions are captured in Equations 2.12 and 2.13, highlighting the complex chemical processes occurring in the combustion chamber that led to NO_x formation. This emphasizes the role of high temperatures in driving the chemical reactions that generate NO_x, which are significant pollutants in engine emissions.



Photochemical smog formation is primarily driven by the presence of NO_x in the atmosphere, a major environmental issue in many large cities worldwide. When

vehicle emissions containing NO_x interact with sunlight and ambient air, they undergo photochemical reactions that contribute to smog formation. In the presence of sunlight, NO_2 breaks down into NO and reactive O atoms. These oxygen atoms then participate in further reactions, leading to the production of smog. This process is represented in Equation 2.14, as discussed by Chen *et al.* (2021), Iavarone & Parente (2020), and Manisalidis *et al.* (2020). The creation of smog not only degrades air quality but also poses significant health and environmental risks, making it a critical concern in urban areas with high vehicular emissions.



2.8 Rationale for Focusing on NO_x Emissions: An Overview from Exhaust Emission Standards

In 1996, a declaration of intent was signed between the U.S. EPA, the California Air Resources Board (CARB), and several prominent diesel engine manufacturers, including Caterpillar, Cummins, Yanmar, Deutz, Detroit Diesel, Isuzu, New Holland, Deere, Komatsu, Kubota, Mitsubishi, and Navistar. The purpose of this agreement was to establish limits on exhaust emissions from various types of diesel engines, including light- and heavy-duty engines, non-road diesel engines, locomotives, and marine engines (US EPA, 2017). The emissions regulated under this declaration on NO_x , CO , HC , and PM , with an emphasis on reducing smoke emissions. As shown in Tables 2.6 and 2.7, which outline the emission standards for non-road diesel engines in the U.S. and the European Union, international regulations have progressively become more stringent over the years. A proposal for "Tier 5" emission standards put forward by the Green Car Congress (2017) aims to set even stricter limits for locomotives. These include a cap of 0.2 g/bhp·hour for NO_x , less than 0.01 g/bhp·hour for particulate matter, and 0.02 g/bhp·hour for HC emissions, with additional GHGs emissions reductions of 10-25% set to take effect by 2025. Hence, in the future, new standards should be established, including all types of exhaust emissions from diesel engines.

Table 2.6 Exhaust emission standards for nonroad diesel engines in the USA (DieselNet, 2023)

Engine rating, P [kW (HP)]	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015-2020						
P < 8 (11)							8.0 / <u>(10.5)</u> / 1.0			8.0 / <u>(7.6)</u> / 0.8							8.0 / <u>(7.5)</u> / 0.4									
8 (11) ≤ P < 19 (25)							6.6 / <u>(9.5)</u> / 0.8			6.6 / <u>(7.5)</u> / 0.8							6.6 / <u>(7.5)</u> / 0.4									
19 (25) ≤ P < 37 (50)							5.5 / <u>(9.5)</u> / 0.8			5.5 / <u>(7.5)</u> / 0.6				5.5 / <u>(7.5)</u> / 0.3					5.5 / <u>(4.7)</u> / 0.03							
37 (50) ≤ P < 56 (75)						- / - / <u>9.2</u> / -				5.0 / <u>(7.5)</u> / 0.4				5.5 / <u>(4.7)</u> / 0.3					5.0 / <u>(4.7)</u> / 0.03							
56 (75) ≤ P < 75 (100)														5.0 / <u>(4.7)</u> / 0.4			5.0 / <u>0.19</u> / <u>0.40</u> / 0.02									
75 (100) ≤ P < 130 (175)				- / - / <u>9.2</u> / -					5.0 / <u>(6.6)</u> / 0.3				5.0 / <u>(4.0)</u> / 0.4													
130 (175) ≤ P < 225 (300)			11.4 / <u>1.3</u> / <u>9.2</u> / 0.54						3.5 / <u>(6.6)</u> / 0.2								3.5 / <u>0.19</u> / <u>2.0</u> / 0.02		3.5 / <u>0.19</u> / <u>0.40</u> / 0.02							
225 (300) ≤ P < 450 (600)		11.4 / <u>1.3</u> / <u>9.2</u> / 0.54						3.5 / <u>(6.4)</u> / 0.2					3.5 / <u>(4.0)</u> / 0.2													
450 (600) ≤ P < 560 (750)		11.4 / <u>1.3</u> / <u>9.2</u> / 0.54						3.5 / <u>(6.4)</u> / 0.2																		
560 (750) ≤ P							11.4 / <u>1.3</u> / <u>9.2</u> / 0.54					3.5 / <u>(6.4)</u> / 0.2					3.5 / <u>0.4</u> / <u>3.5</u> / 0.12			3.5 / <u>0.19</u> / <u>0.35</u> / 0.04						
Pollutant key (g/kWh)																										
CO/HC/NO _x /PM																										
CO/(HC + NO _x)/PM																										
	Unregulated	Tier 1 / Stage I					Tier 2 / Stage II					Tier 3 / Stage IIIA					Tier 4i / Stage IIIB					Tier 4f / Stage IV				

Table 2.7 Exhaust emission standards for nonroad diesel engines for the European Union (DieselNet, 2021)

Engine rating, P [kW (HP)]	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
P < 8 (11)																							8.0 / ~~(7.5)~~ / 0.4		
8 (11) ≤ P < 19 (25)																							6.6 / ~~(7.5)~~ / 0.4		
19 (25) ≤ P < 37 (50)																							5.0 / ~~(4.7)~~ / 0.015		
37 (50) ≤ P < 56 (75)																							5.5 / ~~(7.5)~~ / 0.6		
56 (75) ≤ P < 75 (100)																							5.0 / ~~(4.7)~~ / 0.4		
75 (100) ≤ P < 130 (175)																							5.0 / ~~(4.7)~~ / 0.4		
130 (175) ≤ P < 225 (300)																							5.0 / ~~(4.7)~~ / 0.4		
225 (300) ≤ P < 450 (600)																							5.0 / ~~(4.7)~~ / 0.4		
450 (600) ≤ P < 560 (750)																							5.0 / ~~(4.7)~~ / 0.4		
560 (750) ≤ P																							5.0 / ~~(4.7)~~ / 0.4		
Pollutant key (g/kWh)																									
CO/HC/NO _x /PM																									
CO/(HC + NO _x) /PM																									

Table 2.8 Evolution of NO_x and HC emissions standards for non-road diesel engines across different engine power ratings, regulatory tiers, and regions

Engine rating, P [kW (HP)]	Tier 1 / Stage I	Tier 2 / Stage II	Tier 3 / Stage IIIA	Tier 4i / Stage IIIB	Tier 4f / Stage IV	Stage V (proposed)
P < 8 (11)	10.5	7.5 (28.57%)			7.5	
8 (11) ≤ P < 19 (25)	9.5	7.5 (21.05%)			7.5	
19 (25) ≤ P < 37 (50)	9.5	7.5 (21.05%)	7.5	7.5	4.7 (37.33%)	
37 (50) ≤ P < 56 (75)	9.2	7.5 (18.48%)	4.7 (37.33%)	4.7	4.7	
56 (75) ≤ P < 75 (100)	10.5	8.3 (20.95%)	4.7 (43.37%)	4.7		4.7
75 (100) ≤ P < 130 (175)	10.5	8.3 (20.95%)	4.7 (43.37%)	3.49 (25.74%)	0.59 (83.09%)	0.59
130 (175) ≤ P < 225 (300)	10.5	7 (33.33%)	4 (42.86%)	3.49 (12.75%)	0.59 (83.09%)	0.59
225 (300) ≤ P < 450 (600)	10.5	6.6 (37.14%)	4 (39.39%)	0.59 (85.25%)	0.59	
450 (600) ≤ P < 560 (750)	10.5	6.6 (37.14%)	4 (39.39%)	0.59 (85.25%)	0.59	
560 (750) ≤ P	10.5	6.4 (39.05%)		3.9 (39.06%)	3.69 (5.38%)	

Unit = g/kWh

USA

EU

Table 2.9 Evolution of CO emissions standard for non-road diesel engines across different engine power ratings, regulatory tiers, and regions

Engine rating, P [kW (HP)]	Tier 1 / Stage I	Tier 2 / Stage II	Tier 3 / Stage IIIA	Tier 4i / Stage IIIB	Tier 4f / Stage IV	Stage V (proposed)
P < 8 (11)	8	8			8	8
8 (11) ≤ P < 19 (25)	6.6	6.6			6.6	6.6
19 (25) ≤ P < 37 (50)	5.5	5.5	5.5		5.5	5
37 (50) ≤ P < 56 (75)	6.5	5	5	5	5	5
56 (75) ≤ P < 75 (100)	6.5	5 (23.08%)	5	5	5	5
75 (100) ≤ P < 130 (175)	5	3.5 (30%)	3.5	3.5	3.5	3.5
130 (175) ≤ P < 225 (300)	11.4	3.5 (69.3%)	3.5	3.5	3.5	3.5
225 (300) ≤ P < 450 (600)	11.4	3.5 (69.3%)	3.5	3.5	3.5	3.5
450 (600) ≤ P < 560 (750)	11.4	3.5 (69.3%)	3.5	3.5	3.5	3.5
560 (750) ≤ P	11.4	3.5 (69.3%)	3.5	3.5	3.5	3.5

Unit = g/kWh

USA

EU

The evolution of emission standards for non-road diesel engines highlights distinct trends in the regulation of NO_x, HC, and CO emissions across varying engine power ratings, regulatory tiers, and regions. Importantly, NO_x and HC emissions were measured together for comparison, and NO_x emissions were the predominant contributor compared to HC emissions. Regulations for NO_x emissions have become progressively stricter over time, particularly with the transition from Tier 1/Stage I to Stage V standards. In engines rated between 56 kW and 75 kW, NO_x emissions initially allowed at 10.5 g/kWh under Tier 1 were significantly reduced to 4.7 g/kWh in Tier 3 and eventually to 0.59 g/kWh in Stage V with an impressive 83% reduction. In contrast, CO emissions have shown less variability over the years. Engines with power ratings of 8-19 kW consistently maintained a CO limit of 6.6 g/kWh from Tier 1 through Stage V, reflecting a relatively steady regulatory trajectory. For larger engines rated 130-560 kW, CO emissions were initially set at 11.4 g/kWh under Tier 1. This limit was significantly reduced to 3.5 g/kWh, a 69.3% decrease by Tier 2, with no further reductions in subsequent tiers. When comparing the trends, NO_x emissions stand out as the pollutant with the most aggressive reductions. Meanwhile, the less aggressive approach to CO emissions has resulted in its steady reduction. The focus on NO_x emissions in combined NO_x-HC standards underlines its dominance and critical environmental impact. This emphasis on the selection of NO_x emissions has driven innovation in emission control technologies, ensuring compliance with increasing global regulations.

2.9 Overview of Artificial Neural Network

Computational intelligence (CI), a branch of computer science, is dedicated to developing systems capable of simulating intelligent behaviour. The versatility of ANN has revolutionized fields such as engineering, finance, and healthcare by enabling innovative solutions to complex problems. Their capacity to adapt to diverse datasets and problem domains underscores their significance within CI and highlights their potential for advancing data-driven methodologies and decision-making systems. Among its prominent techniques, ANN has emerged as a powerful tool for tasks such as pattern recognition and function approximation. Unlike traditional statistical methods, which often rely on predefined assumptions, ANN adapts dynamically to

data, offering flexible and realistic solutions (Abiodun *et al.*, 2018; Chen *et al.*, 2024; Yu & Zhu, 2020). This adaptability allows ANN to serve as universal approximators, effectively learning from historical data and generalizing to predict or classify new information (De Simio *et al.*, 2023; Viana *et al.*, 2023). Inspired by the structure and functionality of the human brain, an ANN replicates its ability to process complex information through interconnected layers of mathematical computations. This biologically inspired design equips ANN to handle nonlinear relationships in data, making it suitable for a wide array of applications. Their performance is typically evaluated based on factors such as accuracy, processing speed, clustering efficiency, classification precision, and overall system reliability (Abdolrasol *et al.*, 2021; Alaloul *et al.*, 2020; Din *et al.*, 2024).

The term "neural" in ANN is derived from the basic functional units of the nervous system: neurons or nerve cells found in the brain and throughout the body. ANN are computational models designed to simulate the way the human brain processes information, identifying patterns and relationships within datasets. Like the brain, ANN adjusts inputs to optimize outputs without needing to redesign the entire process, enabling it to effectively model real-world scenarios (S. F. Ahmed *et al.*, 2023; Bogatenko *et al.*, 2023; Zador *et al.*, 2023). In the human brain, neurons are interconnected to form a complex and dynamic network that controls the nervous system. Communication between neurons establishes strong connections, allowing signals to be transmitted and adapted. Similarly, dendrites collect signals from connected neurons, which are then processed and modified to improve learning in an ANN. Axons transmit these signals, completing the cycle of communication and learning within the network (Bogatenko *et al.*, 2023; López *et al.*, 2022). This brain-inspired structure makes ANN highly effective for modelling and forecasting tasks such as predicting power output in marine diesel engines. By emulating the learning processes of the brain, an ANN can handle complex relationships in data and adapt to new information over time. Figure 2.7 presents a typical neuron offering a simplified representation of the ANN architecture that underpins these powerful models.

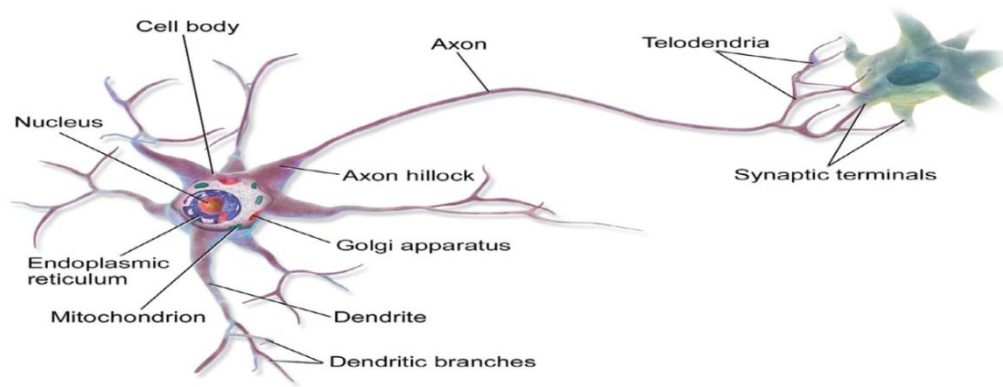


Figure 2.7 Typical nerve cell as a simple representation of ANN architecture (López *et al.*, 2022)

In the human brain, dendrites receive signals from other neurons, the cell body processes and trains these inputs, and the axon transmits the processed information as output. This structure is replicated in an ANN where the dendrites correspond to the input data, the cell body processes the data, and the axon represents the model's output. The brain serves as a control center that interprets complex information and makes decisions, and this ability is mirrored in the design of an ANN. By simulating the brain's process, ANN can handle complex data interpretation and decision-making tasks effectively (Bogatenko *et al.*, 2023; Shao & Shen, 2022; Taherdoost, 2023). ANN is widely applied in fields such as medical diagnosis, voice and facial recognition, data recovery, and more. These networks are particularly effective in solving intricate problems like data classification and pattern recognition, as the neural learning process allows them to detect subtle patterns within large datasets (Liu *et al.*, 2023; Sun *et al.*, 2024; Zador *et al.*, 2023). A basic ANN component, including the perceptron, receives real-valued inputs in the form of vectors. These inputs are processed through linear combinations, and the model outputs either 1 if the value exceeds a threshold or -1 if it does not. Figure 2.8 illustrates a perceptron and its mathematical notation, demonstrating the fundamental operation of this key ANN element.

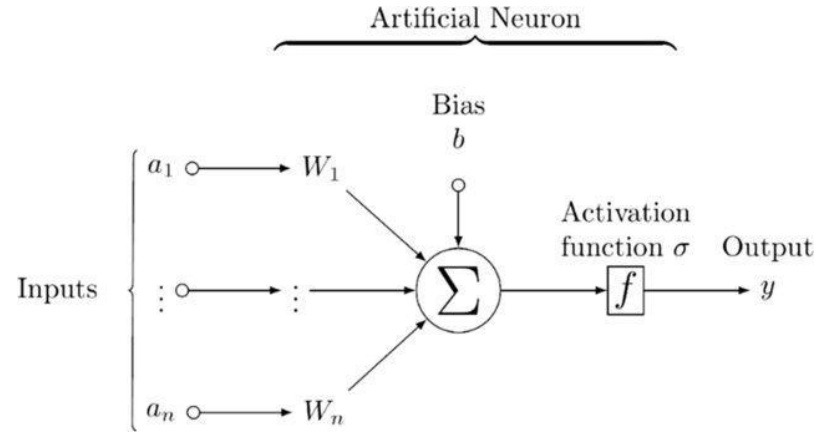


Figure 2.8 Representation of a perceptron (Cieslak *et al.*, 2020)

Referring to Figure 2.9, let the real-valued inputs x_1 to x_n , and the output be $o(x_1, \dots, x_n)$, then the calculated perceptron is given by Eq. 2.15.

$$\begin{aligned}
 o(x_1, \dots, x_n) &= 1 && \text{if } w_0 + w_1x_1 + \dots + w_nx_n > 0 \\
 &= -1 && \text{otherwise}
 \end{aligned} \tag{Eq. 2.15}$$

Where w_i is a weight or real-valued constant.

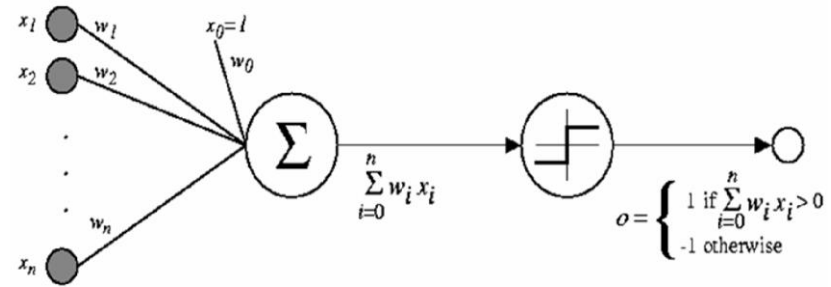


Figure 2.9 Mathematical representation of a perceptron (Hounmenou *et al.*, 2021)

In a perceptron, the quantity $(-w_0)$ represents the threshold that the weighted sum of inputs $w_1x_1 + \dots + w_nx_n$ must exceed for the perceptron to output a 1. To simplify the notation, an additional constant input was introduced as $x_0 = 1$, which allows the inequality to be written as:

$$\sum_{i=0}^n w_i x_i > 0 \quad (\text{Eq. 2.16})$$

In this formulation, the perceptron's learning process involves adjusting the weights $w_0, w_1, \dots, w_n$ to correctly classify input data. By iteratively refining these weights during training, the perceptron learns to make predictions that align with the desired outputs. This process is fundamental to the operation of artificial neural networks, where the goal is to optimize the weights to improve the model's performance in tasks such as classification and pattern recognition.

The three-layer architecture comprising the input, hidden, and output layers is a fundamental structure in ANN. As depicted in Figure 2.10, the network begins with the input layer, progresses through the hidden layer, and culminates in the output layer. The main objective of an ANN is to transform the inputs into meaningful outputs. The input layer consists of units that collect raw data such as engine speed, load, power, and exhaust emissions (Abiodun *et al.*, 2018; H. Liu *et al.*, 2023; Sayyed *et al.*, 2021). These inputs are then passed to the hidden layer, where nodes are activated based on signals received from the input units. The hidden layer involves complex interactions between these nodes, with each connection assigned a weight that dictates the strength of the relationship between inputs and nodes. The output layer processes the weighted interactions from the hidden layer and produces the result. In the context of emissions forecasting, the output layer generates predictions of pollutant concentrations based on the relationships between input parameters such as power, load, and speed (Alaloul *et al.*, 2020; López *et al.*, 2022). This architecture enables ANN to effectively model complex and nonlinear relationships, thus making accurate predictions, and is ideal for applications such as emissions estimation in diesel engines.

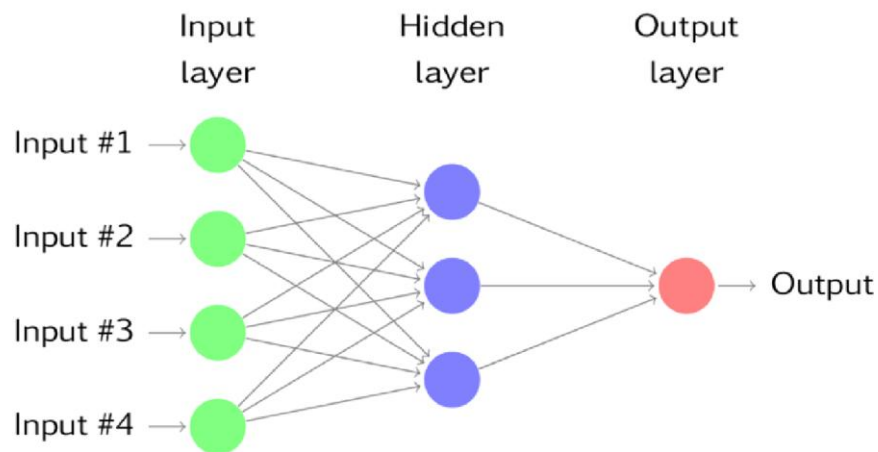


Figure 2.10 ANN architecture (Hounmenou *et al.*,2021)

2.9.1 NO_x Prediction by Artificial Neural Network

This section examines the application of ANN in predicting emissions and performance metrics from diesel engines with a primary focus on NO_x emissions. The objective is to highlight the predictive capabilities of ANN in accurately modelling NO_x emissions while also addressing its versatility in estimating other critical engine performance and emission parameters across diverse environmental and operating conditions. ANN has demonstrated an exceptional ability to model the intricate and nonlinear relationships among variables such as engine speed, load, fuel type, and exhaust emissions. These models offer insights into how variations in operating conditions influence NO_x formation, making them invaluable tools for real-world applications. In addition to NO_x emissions, ANN has been employed to predict other emissions, including CO, CO₂, and HC. Furthermore, ANN models are capable of estimating performance parameters such as power output, BSFC, and BTE. This multifaceted approach makes ANN a powerful tool for comprehensive diesel engine analysis, addressing both environmental and operational goals. Table 2.10 summarizes the previous results of applying the ANN method for modelling.

Table 2.10 Comparison of ANN model configurations and performance metrics for predicting NO_x emissions and other related parameters of a diesel engine

Type of learning algorithm	Optimum neuron number	Emissions						Performance		References
		NO _x	CO	CO ₂	HC	Smoke	BSFC	BTE		
LM	15	R ² =0.99526 RMSE=0.0047	R ² =0.99945 RMSE=0.0084	R ² =0.99964 RMSE=0.0036	R ² =0.99977 RMSE=0.027	R ² =0.99998 RMSE=0.0259	R ² =0.99963 RMSE=0.0034	R ² =0.99843 RMSE=0.0094	Kumar <i>et al.</i> , 2020	
LM	50	R ² =0.94012	R ² =0.93577	-	R ² =0.89593	-	-	R ² =0.96423	Kumar <i>et al.</i> , 2024	
LM	100	R ² =0.9891 RMSE=188.284	-	-	-	R ² =0.97467 RMSE=10.82514	R ² =0.99801 RMSE=0.01531	R ² =0.99803 RMSE=1.3843	Mohan <i>et al.</i> , 2024	
LM	7	-	-	-	-	R ² =0.9901 RMSE=2.0388	R ² =0.9994 RMSE=0.03162	R ² =0.9146 RMSE=0.8749	Patnaik <i>et al.</i> , 2024	
LM	40	R ² =0.86 RMSE=0.0453	-	R ² =0.93 RMSE=0.0533	-	-	-	-	Domínguez-Sáez <i>et al.</i> , 2018	
LM	25	R ² =0.999	R ² =0.9989	-	R ² =0.9883	-	R ² =0.999	R ² =0.9994	Raghuvaran <i>et al.</i> , 2021	
BP	25	R ² =0.87	R ² =0.89	R ² =0.92	R ² =0.97	-	R ² =0.93	-	Soufi <i>et al.</i> , 2015	
LM	23	R ² =0.998 RMSE=0.0316	R ² =0.9604 RMSE=0.1414	R ² =0.998 RMSE=0.0316	R ² =0.9702 RMSE=0.1225	R ² =0.998 RMSE=0.0316	R ² =0.9604 RMSE=0.1414	R ² =0.998 RMSE=0.00316	Prasada Rao <i>et al.</i> , 2017	
LM	17	R ² =0.9912 RMSE=4.89	R ² =0.82724 RMSE=0.0063	-	R ² =0.99519 RMSE=0.54	R ² =0.99549 RMSE=0.0653	-	R ² =0.997 RMSE=0.48	Subramanian <i>et al.</i> , 2021	

The evaluation of ANN configurations and the effectiveness in predicting diesel engine emissions, including NO_x, CO, CO₂, HC, smoke, BSFC, and BTE, provides a valuable understanding. The LM method stands out for its reliability and fast convergence, consistently outperforming backpropagation in accuracy and robustness across multiple emission parameters. The architecture of the ANN, particularly the number of neurons in the hidden layer, plays a critical role in prediction performance. Studies reveal that optimal neuron counts typically range between 7 and 100, yield varying levels of accuracy depending on the emission parameter and dataset. Mohan *et al.* (2024) used 100 neurons and achieved high precision for NO_x predictions ($R^2 = 0.9891$), though such high neuron counts may risk overfitting for other outputs. On the other hand, smaller configurations like the 7-neuron model by Patnaik *et al.* (2024) demonstrated adequate performance but lacked the precision needed for certain emission predictions. ANN models particularly excel in predicting NO_x emissions with reported R^2 ranging from 0.86 to as high as 0.999. The ability of the model to maintain low root mean square error (RMSE) values further highlights its predictive accuracy. Lower RMSE values indicate a closer match between predicted and actual emission data, with the most effective models achieving RMSE values near zero, underscoring the capacity of ANN to minimize prediction errors and enhance reliability. These findings reinforce the potential of ANN-based approaches, especially when optimized for neuron counts and learning algorithms to deliver accurate and flexible models for predicting a wide range of diesel engine emissions and performance metrics. This highlights the adaptability of ANN in addressing the complexity of engine emissions under diverse operating conditions.

Figure 2.11 shows the comparison data of exhaust emissions predicted by the ANN and obtained by the experimental research by Agudelo *et al.* (2013). Excellent results have been obtained from the ANN models used to estimate exhaust emission characteristics, with a value of R^2 more than 0.99 for all parameters. The value of R^2 for NO_x emission is 0.9954, followed by 0.9944, 0.992, and 0.9916 for CO, smoke opacity, and CO₂ production, respectively. Venkatesh *et al.* (2023) observed that the ANN model was able to predict exhaust emission quite well, with the regression coefficient lying closer to 1 with mean square error (MSE) was found to be very low.

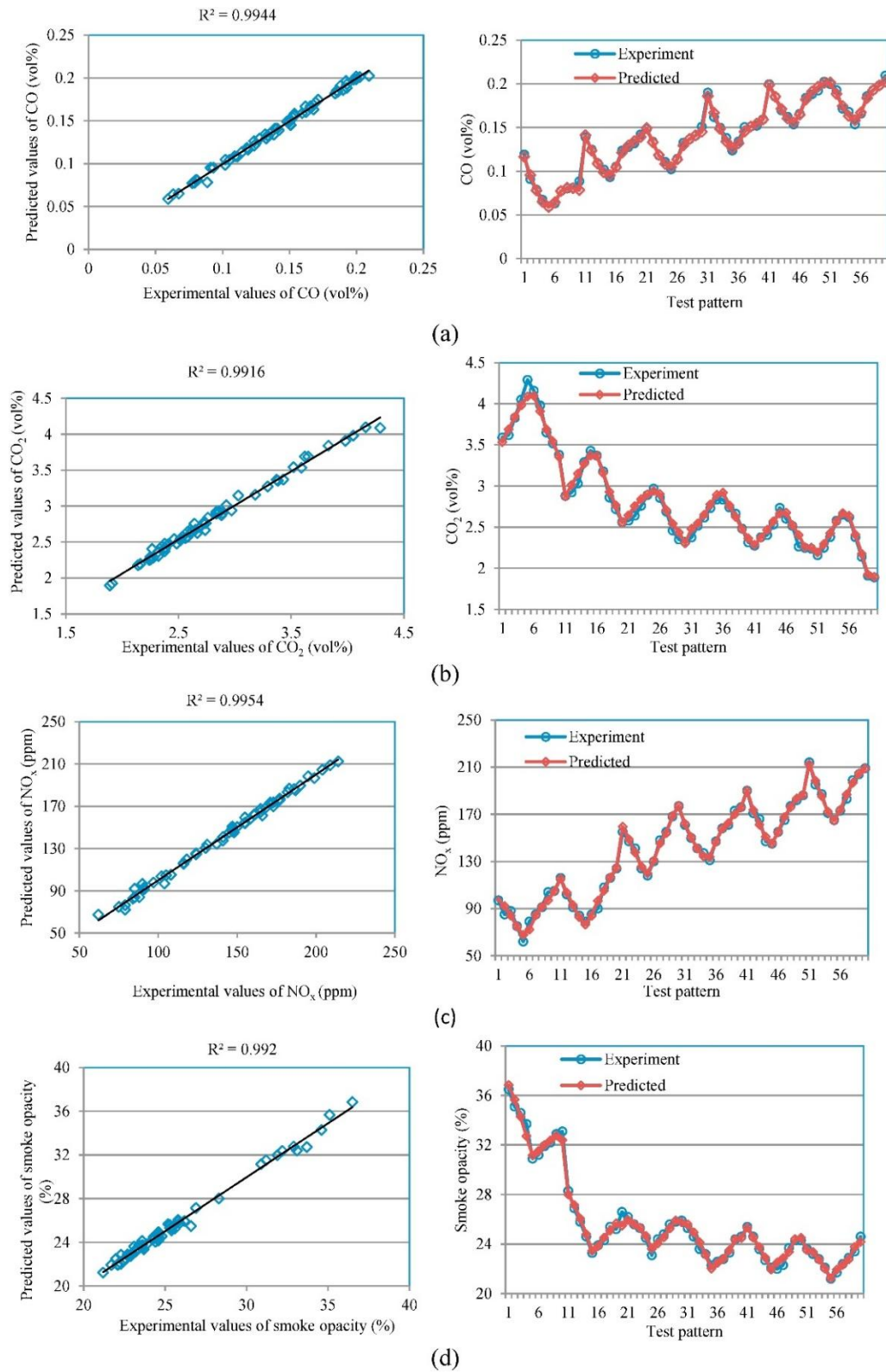


Figure 2.11 Comparison between data predicted by the ANN model and the data obtained from experiments for exhaust emission parameters: (a) NO_x , (b) CO, (c) CO_2 , and (d) smoke opacity (Agudelo *et al.*, 2013)

ANN is becoming more popular because of its capability to handle complicated decision-making, reduce the manual work needed, and make processes more efficient. They learn from large datasets to spot patterns and make smart decisions, which is incredibly useful for tasks like forecasting, classifying data, and optimizing systems. ANN has become indispensable across diverse industries. In manufacturing, ANN were used to monitor production quality and keep equipment running smoothly. In automotive and transport, ANN helps with self-driving technologies, traffic predictions, and even emissions modelling (Shaygan *et al.*, 2022; Tercan & Meisen, 2022; Zonta *et al.*, 2022). Finance applied ANN for fraud detection and predicting market trends, while healthcare relies on everything from diagnostics to personalized treatment plans (Ahmed *et al.*, 2022; du Preez *et al.*, 2025). ANN is also playing a big part in energy and environmental work, like predicting emissions, managing fuel combustion, and integrating renewable energy sources (Al-Othman *et al.*, 2022; Moon *et al.*, 2019; Nanlohy *et al.*, 2024). In agriculture, ANN were used for things like predicting crop yields and spotting diseases. Retail companies use ANN to understand what customers want and plan inventory, and in telecommunications, ANN is key to keeping networks running smoothly (Abbasi *et al.*, 2021; Wang *et al.*, 2021). In cybersecurity, ANN helps spot unusual behaviour and keep systems safe (Mebawondu *et al.*, 2020; Sowmya & Mary Anita, 2023). This flexibility and ability to tackle complex problems make ANN such a valuable tool across so many different fields.

CHAPTER 3

METHODOLOGY

This chapter outlines the comprehensive research methodology adopted to achieve the objectives outlined in Chapter 1. The methodology flowchart presented in Figure 3.1 illustrates the structured approach beginning with experimental research conducted using the Yanmar L48N6-MTMRYI diesel engine. The experiments were performed at a constant speed following the weighting factors of the B-Type ISO 8178 standard for Type D2 engines. The research evaluated various diesel fuels, including B0 as the baseline fuel, a blend containing 10% palm oil biodiesel by volume (B10), and plastic-derived diesel fuels blended with 10% polypropylene (PP10) and high-density polyethylene (HDPE10). The B10 blend was sourced from a local fuel station, while the plastic-derived diesel samples were provided by Syngas Sdn. Bhd. The research methodology began with a survey and the preparation of the fuel samples. The plastic-derived diesel fuels underwent a series of property evaluations, including FTIR spectroscopy, bomb calorimeter, viscosity, GC-FID, and CHNS element analyses. These assessments ensured the fuels met the required standards and provided critical data on their composition and energy content. Subsequently, all fuel types were tested in the diesel engine to analyse trends in engine performance and exhaust emissions. The experimental data were then modelled using MLP models to predict NO_x emissions. Finally, the performance of the developed models was evaluated using accuracy and error metrics, identifying the best-fit model based on its predictive reliability and effectiveness. This systematic approach ensures a robust understanding of the relationship between alternative diesel fuels, engine performance, and emissions while leveraging MLP modelling to enhance the prediction and analysis of NO_x emissions.

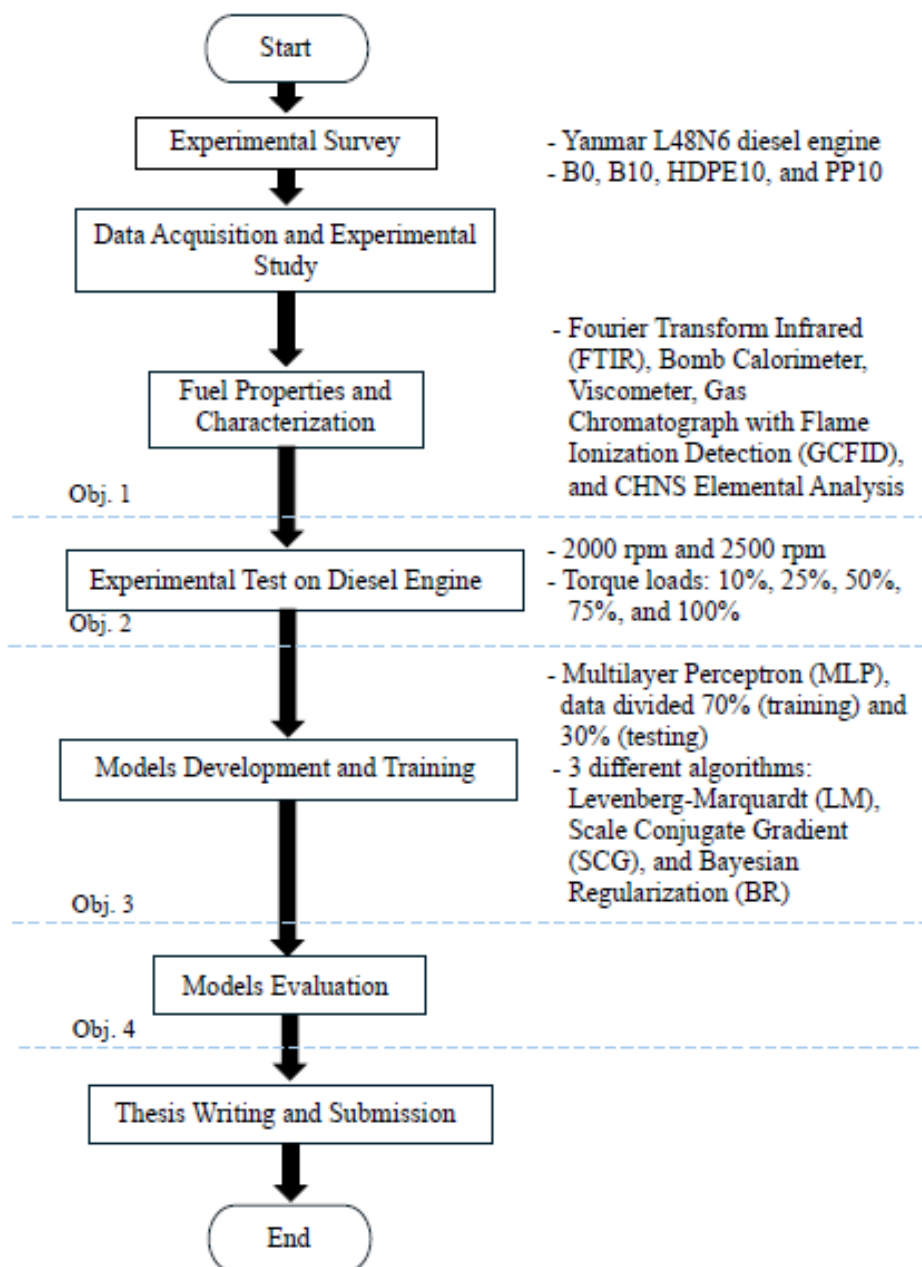


Figure 3.1 Flowchart of the research

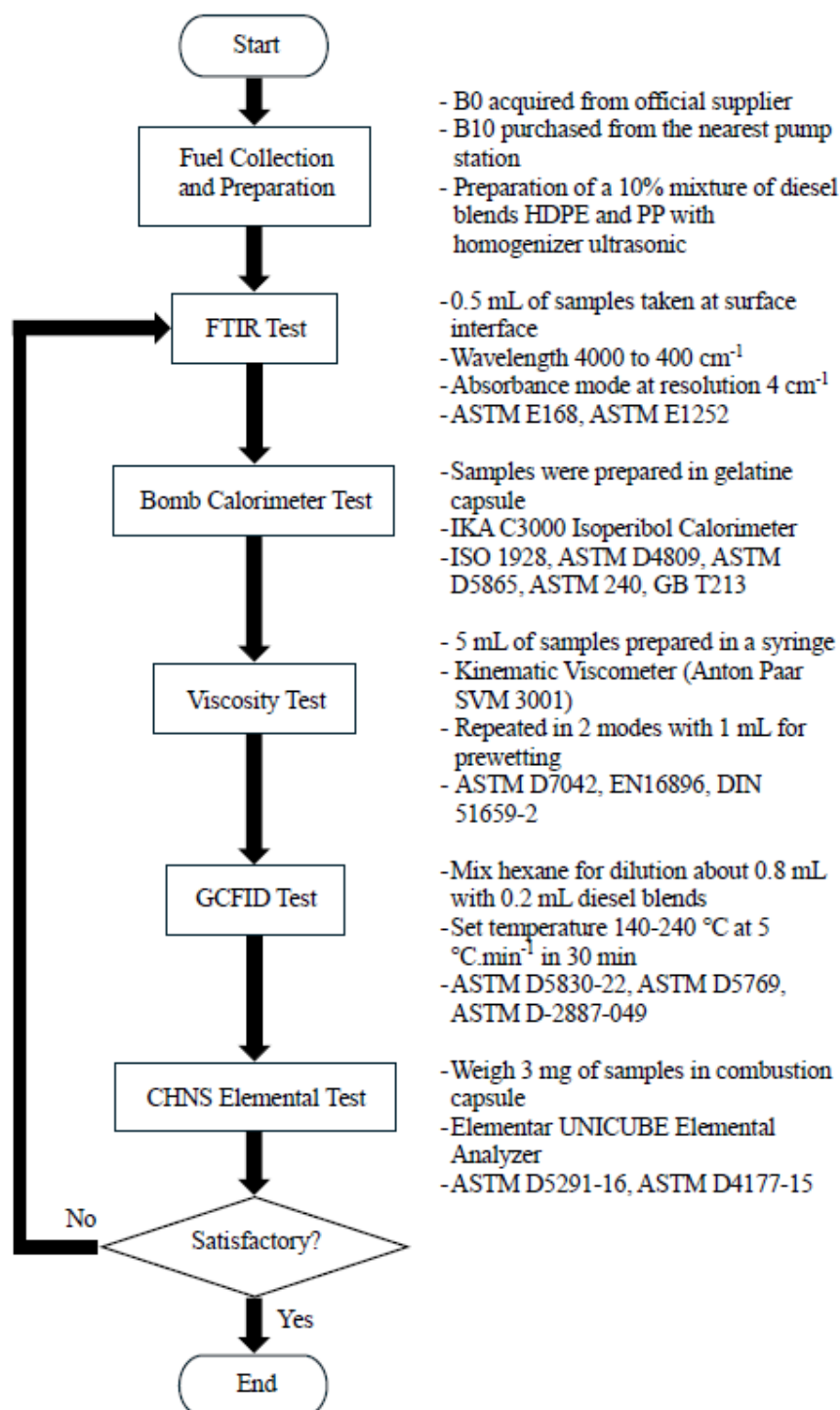


Figure 3.2 Flowchart for characterization of biodiesel fuels

3.1 Fuel Preparation

Figure 3.2 provides a simplified flowchart describing the process of characterizing and preparing the diesel fuel blends used. B0 was acquired from an official supplier, ensuring its compliance with industry standards for quality and performance. The biodiesel blend, B10, which contains 10% palm oil methyl ester, was sourced from a nearby fuel station. Certificates of quality for these fuels are attached as Appendices 1 and 2 for validation purposes. For the plastic-derived diesel fuels, HDPE and PP were selected due to their high availability in plastic waste streams and their potential to produce alternative diesel fuels. The plastic-derived diesel was acquired from Syngas Sdn. Bhd, located at Gong Badak Industrial Park. Preparing plastic-derived diesel fuels involved several challenges. First, the quality and consistency of the raw plastic waste were major concerns. Variability in the plastic feedstock, such as contamination with food residues or mixed polymers, affected fuel yield and quality. This required rigorous sorting and pre-treatment to reduce impurities. Second, the pyrolysis process needed careful optimization. Key factors such as temperature, reaction time, and catalyst use had to be carefully controlled to maximize the diesel fraction while minimizing undesirable byproducts like waxes and tars, ensuring consistent fuel properties. Finally, after production, the plastic-derived diesel fuels underwent a series of tests to ensure compatibility with diesel engines and confirm that the fuels met the necessary standards for blending and combustion (Jeremiah *et al.*, 2023).

The fuel preparation involved hands-on lab work to create consistent and reliable fuel blends. Plastic-derived diesel fuels from HDPE and PP were each mixed with B0 at a 10% volume ratio, producing the HDPE10 and PP10 blends. This ratio was chosen to allow a fair comparison with the commonly used B10 blend, which contains 10% palm-based biodiesel. These blends helped assess whether plastic-derived fuels could serve as practical alternatives to traditional biodiesel in diesel engines. To prepare the blends, 200 mL of plastic-based diesel was added to 1800 mL of B0 in a clean container. The mixture was then blended using a handheld ultrasonic homogenizer (MT-30K, 50Hz) operated at $5,000 \pm 100$ rpm for 5 ± 1 minutes. This process ensured that the fuels were well-mixed and stable for testing. The fuels were stored in sealed,

labelled containers to keep them clean and ready for engine testing. This careful preparation helped ensure accurate and consistent results throughout the research.

Preparing plastic-derived diesel fuels and ensuring proper blending presented several challenges. One key issue was the variability in plastic waste composition, which can include different types of polymers and contaminants. This inconsistency could result in fuel properties, like the presence of impurities could complicate the blending process (Qureshi *et al.*, 2020). To address this, careful sorting and pre-treatment of the plastic waste were essential before the pyrolysis process, though this was time-consuming. Another challenge was the potential for phase separation during blending. Plastic-derived diesel fuels have different physical properties compared to conventional diesel. This can cause incomplete blending. Using an ultrasonic homogenizer helped achieve better fuel uniformity and prevent this issue. Maintaining the stability of the blends over time was also critical. Due to the complex chemical makeup of plastic-derived fuels, there was a risk of separation or instability, particularly under varying temperature conditions. Regular checks were necessary to ensure the blends remained stable throughout the testing phase. Finally, contamination was a concern as traces of chemicals from the pyrolysis process could affect the quality of the final blend. To avoid contamination, all equipment used in the blending process, such as containers and homogenizers, was thoroughly cleaned and maintained to ensure the integrity of the fuel samples. Figure 3.3 illustrates the various biodiesel blends, including those containing HDPE and PP plastic-derived diesel fuels.



Figure 3.3 Visual comparison of six diesel fuel samples

3.2 Fuel Properties Characterization

This section provides an overview of the physical and chemical properties of the diesel fuels used in the experiment. Characterizing the fuel properties is crucial for understanding how different fuel types, particularly plastic-derived diesel fuels, interact with the diesel engine in terms of performance, emission behaviour, and overall engine efficiency. This section outlines the procedures used to assess the viscosity, calorific value, and chemical composition, which influence fuel behaviour during engine operation. By doing the tests, the fuel blends are ensured to comprise B0, B10, HDPE10, and PP10. These were adequately characterized by their sustainability in engine operation and impact on emissions and performance. The results of these characterizations form the foundation for subsequent experimental analysis and modelling, allowing for the accurate prediction of performance and emissions under various operating conditions.

3.2.1 Fourier Transform Infrared Spectrometer

FTIR spectroscopy is a powerful technique used to identify functional groups, molecular bonds, and intermolecular interactions within a sample. It is particularly effective for confirming the purity of a compound and detecting the presence of impurities or secondary chemical groups. The mid-infrared spectra of all fuel samples were analysed using an Agilent Technologies Cary 630 FTIR spectrometer, as shown in Figure 3.4. This advanced spectrometer features an attenuated total reflectance (ATR) interface system enabling precise analysis over a spectral range of 4000 to 400 cm^{-1} . For each analysis, 0.5 mL of the fuel sample was applied directly onto the ATR interface. The spectra were recorded in absorbance mode at a resolution of 4 cm^{-1} , ensuring high accuracy and clarity in identifying molecular characteristics. Before the analysis, the instrument was calibrated using the FTIR spectrum of distilled water to ensure measurement reliability and consistency. FTIR spectroscopy was used to characterize the molecular composition of all tested fuels, including B0, B10, HDPE10, and PP10. This characterization provided critical insights into the chemical structures and helped identify any impurities or variations in the fuel blends.



Figure 3.4 FTIR spectrometer (Agilent Technologies Cary 630)

3.2.2 Bomb Calorific Value

The calorific value of the fuel blends was determined using a bomb calorimeter (IKA C3000 Isoperibol Calorimeter) as shown in Figure 3.5. This instrument measures the energy released during the complete combustion of a fuel sample, providing essential insights into its energy content. The process began with the fuel sample being carefully placed in a gelatin capsule and weighed. The capsule was then transferred to a crucible, where a cotton thread was attached to facilitate ignition. The crucible was connected to the ignition wire using another cotton thread to ensure efficient combustion. The vessel was tightly sealed and placed in the bomb chamber, which was filled with oxygen at a pressure of 40 bar to enable complete and controlled combustion to start the process. The sample was ignited, and the heat released during combustion was measured and recorded as the gross calorific value (H_0). The gross calorific value represents the total amount of heat liberated during complete combustion, normalized to the weight of the fuel sample. For fuel blends containing water, it was ensured that any water present in the compounds remained in a liquid state after combustion. The net calorific value was calculated based on the gross calorific value and additional analysis data following internationally recognized standards. The procedures adhered to protocols outlined in ISO 1928, ASTM D4809, ASTM D5865, ASTM D240, and GB/T213, ensuring accuracy and reliability. This

calorific value analysis was critical in evaluating the energy content of the tested fuel blends, for B0, B10, HDPE 10, and PP10.



Figure 3.5 IKA Calorimeter C3000 and decomposition vessel with crucible

3.2.3 Kinematic Viscometer and Density

The kinematic viscosity and density measurements were performed using the Anton Paar SVM 3001 portable viscometer, as shown in Figure 3.6. This state-of-the-art device is specifically designed to measure dynamic viscosity, kinematic viscosity, and density, making it an ideal tool for characterizing liquid fuels. For each sample, approximately 5 mL of fuel was drawn into a syringe and carefully transferred to the viscometer's measuring cell. To ensure precision, the testing process included two repeated measurements, with 1 mL of the sample used for prewetting the measuring cell before testing. The results were reported as the average of the two measurements. The SVM 3001 viscometer was calibrated in compliance with internationally recognized standards, including ASTM D7042, EN 16896, and DIN 51659-2, ensuring the measurements were both accurate and reproducible. This rigorous adherence to global standards underscored the reliability of the data collected. The results of these tests provided valuable insights into the physical properties of the tested fuel blends. Kinematic viscosity and density are important for assessing the flow characteristics and fuel quality.



Figure 3.6 Portable kinematic viscometer (Anton Paar SVM 3001)

3.2.4 Gas Chromatograph Flame Ion Detector

The Shimadzu GC-2010 Plus GC-FID shown in Figure 3.7 was employed to analyse the chemical composition of the diesel blends. The system was equipped with a ZB-MS5 column (Agilent) featuring dimensions of 30 m x 0.25 mm and a film thickness of 0.25 μm , allowing precise separation of the fuel components. The samples were prepared by mixing diesel blends with hexane at a 1:4 ratio, and 1 μL of the solution was injected into the system. The column temperature program was carefully optimized for effective separation. It started at 80°C, maintained for 5 minutes, and then increased at a rate of 8°C/min to reach 170°C, where it was held for 10 minutes. The temperature was further raised by 8°C/min to 250°C and held for another 10 minutes, followed by a final increase of 10°C/min to 300°C, where it was maintained for 10 minutes to ensure complete analysis. The injector temperature was set to 280°C, and the detector temperature was maintained at 320°C. Helium was used as the carrier gas at a flow rate of 1.26 mL/min with a split ratio of 1:20 to ensure precise and reproducible sample injection. To ensure accuracy and reliability, each batch of analysis included six samples along with a hexane blank to monitor system stability.

The response factors of the diesel blend relative to the internal standard were calculated a minimum of three times for each sample to ensure consistency and repeatability. This thorough and standardized process provided a detailed chemical profile of the diesel blends.



Figure 3.7 Shimadzu GC-2010 Plus

3.2.5 CHNS Elemental

The Elementar UNICUBE elemental analyser, as shown in Figure 3.8, was used to determine the elemental composition of carbon (C), hydrogen (H), nitrogen (N), sulphur (S), and oxygen (O) of the fuel blends, which is critical for evaluating combustion properties and emission behaviour. This analysis is essential for understanding how the fuel performs in terms of energy content, combustion efficiency, and environmental impact. To perform the analysis, approximately 1-2 mg of the fuel sample was precisely weighed and placed in a ceramic crucible. The sample was combusted in an oxygen-rich environment at a temperature of 1,100°C. During combustion, the elements in the fuel, C, H, N, S, and O elements were oxidized into their respective gaseous products: CO₂, H₂O (water vapour), sulphur dioxide (SO₂), and NO_x. These gases were then analysed using infrared detectors for CO₂ and H₂O, chemiluminescence detectors for NO_x, and specific sulphur detectors for SO₂. The data obtained from these detectors were used to calculate the exact elemental composition

of the fuel sample. The analysis was conducted following ASTM D5291-16 for determining the C, H, and N content and ASTM D4177-15 for S determination. Calibration with standard reference materials was performed to ensure measurement accuracy. The results provided the precise percentages of each element in the fuel for understanding the fuel's combustion efficiency, potential emissions, and overall suitability for diesel engine applications.



Figure 3.8 Elementar UNICUBE elemental analyser

3.3 Engine Testing

Engine testing is a fundamental process in the development and optimization of propulsion systems, particularly in mechanical and automotive engineering. These tests provide insights into engine operation and reveal the complex mechanisms that drive modern transportation. To achieve optimal performance, fuel efficiency, and reliability, engines are subjected to rigorous evaluations that examine their capabilities and limitations under various conditions. These analyses play a vital role in guiding engine design improvements and ensuring adherence to performance and emissions regulations. Figure 3.9 illustrates a streamlined flowchart outlining the methodology used to assess the performance and emissions of biodiesel fuels. This comprehensive testing process comprises multiple stages, each contributing to the development of reliable and efficient engine systems. It enables researchers and manufacturers to ensure that engines and fuel blends meet regulatory requirements, performance benchmarks, and user expectations. The Yanmar L48N6-MTMRYMI diesel engine

was utilized, equipped with an SPTC Autochek GP-20G gas analyser for exhaust emissions measurement. Additionally, a dyno controller integrated with DM6 software was employed to monitor engine performance in real time. This testing setup provided accurate and reliable data, forming the basis for evaluating the performance and environmental impact of the biodiesel blends under investigation.

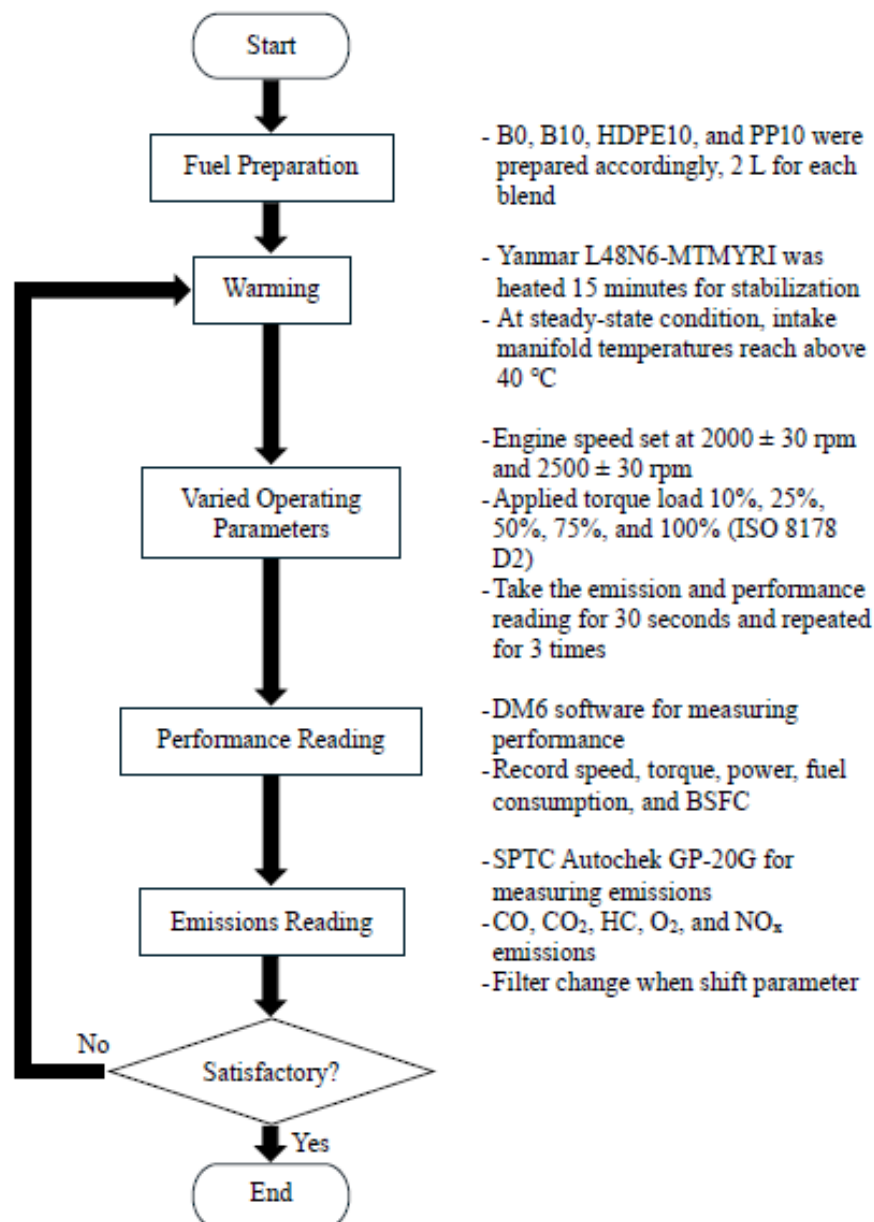


Figure 3.9 Flowchart for assessing the trend of performance and emissions from biodiesel fuels

3.3.1 Engine Specifications

Engine testing was performed using the Yanmar L48N6-MTMYI diesel engine with its physical setup and schematic diagram illustrated in Figures 3.10 and 3.11, respectively. This 4-stroke, vertical-cylinder Yanmar diesel engine features an advanced direct injection system ensuring precise fuel atomization and efficient combustion, making it ideal for evaluating fuel performance and emissions. The engine was equipped with critical instruments, including an emission analyser and a data acquisition system to capture real-time data on its performance and exhaust emissions. Before data collection, the engine underwent a warm-up period to stabilize its operating conditions and ensure consistent and reliable results. This step was essential to minimize variations caused by temperature or transient operation. Detailed specifications of the Yanmar L48N6-MTMYI engine are provided in Table 3.1, outlining its key parameters and technical capabilities. These specifications highlight the suitability for testing biodiesel and alternative diesel blends, ensuring an accurate assessment of their impact on engine performance and emissions.

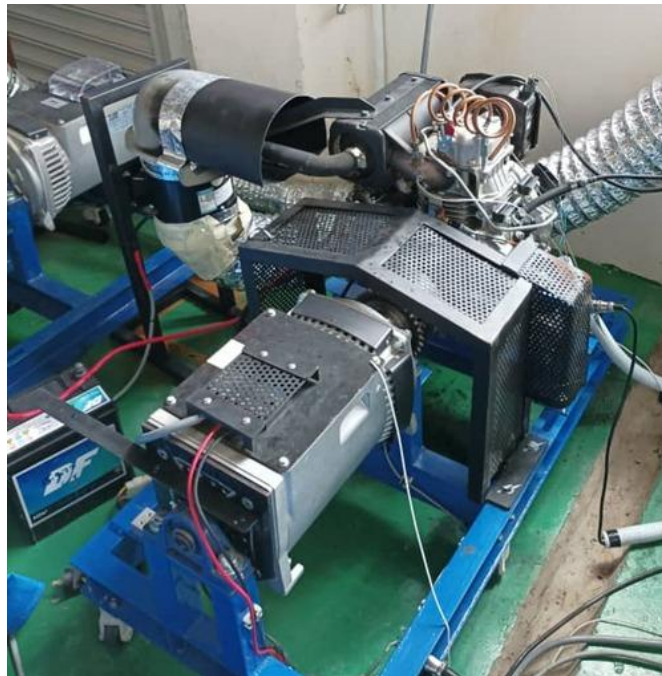


Figure 3.10 Yanmar L48N6-MTMYI diesel engine model

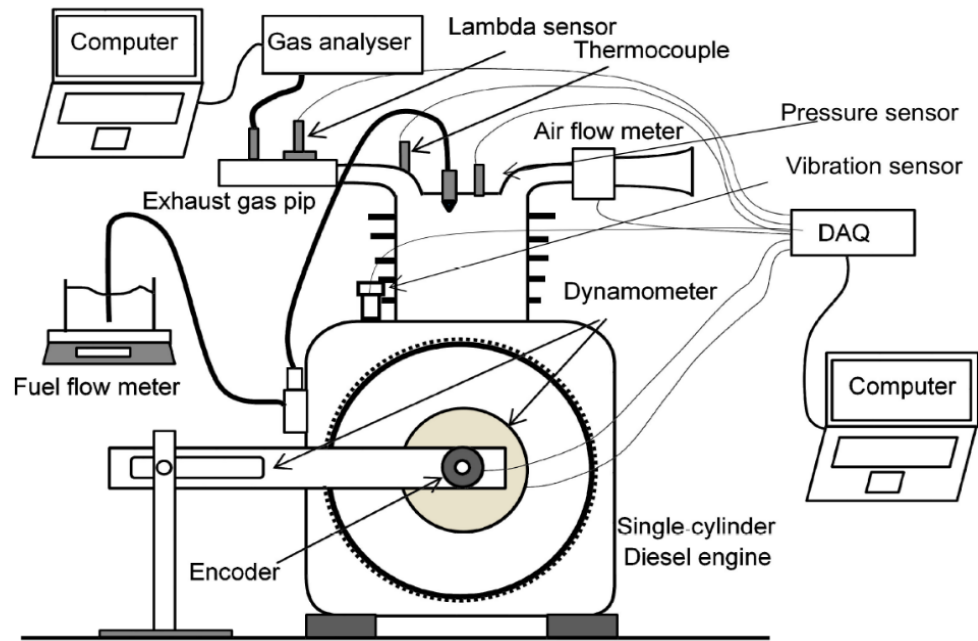


Figure 3.11 Schematic diagram of Yanmar L48N6-MTMRYI diesel engine

Table 3.1 General specification, performance, and technical data of Yanmar L48N6-MTMRYI

Specifications		Yanmar L48N6-MTMRYI	
Engine series		L-N series	
Engine type		4-stroke, vertical cylinder, air-cooled diesel engine	
Number of cylinders		1	
Bore x Stroke		70 mm x 57 mm	
Displacement		0.219 Liter	
Continuous rated output	Engine speed	3600 rpm	3000 rpm
	Output	3.1 kW	2.8 kW
Maximum rated output	Engine speed	3600 rpm	3000 rpm
	Output	3.5 kW	3.1 kW
High idling		3800±30 rpm	3175±30 rpm
Engine weight (dry)	Electric starter	32 kg	
	Recoil starts	27kg	
Cooling system		Forced air-cooling by a flywheel fan	
Lubricating system		Forced lubricating system	
Starting system		Electric start / Recoil starts	
Dimension		332 mm (L) x 384 mm (W) x 417 mm (H)	
Fuel oil tank capacity		2.4 Liter	

The Yanmar L48N6-MTMYRI diesel engine was tested following the Type D2 standard, following the Weighting Factors of the B-Type ISO 8178 Test Cycle, a globally recognized standard for measuring exhaust emissions from non-road engines. It provides a structured and repeatable methodology for measuring pollutants and is widely used for type approval and emission certification testing, ensuring consistency and reliability in evaluating engine performance. The application of ISO 8178 ensures that emission measurements are conducted under representative engine operating conditions using a defined set of load and speed points. The Type D2 cycle is used for constant-speed engines and is widely employed in both regulatory types of approval and emission certification testing, ensuring standardization, scientific integrity, realistic engine assessment, and regulatory relevance.

The testing protocol involved applying five engine loads: 10%, 25%, 50%, 75%, and 100% of the engine's maximum load capacity. These loads were applied at two constant intermediate speeds of 2000 rpm and 2500 rpm, with intermediate speed defined as the engine speed at which maximum torque is achieved, taking the reading 30 seconds repeated 3 times for each load and speed applied. The engine speed was precisely controlled using the throttle position lever to maintain stable conditions during testing. Baseline measurements were taken at the nominal spray angle preset by the engine, and data were collected at each of the specified load levels. Table 3.2 provides an overview of the engine operating modes and the corresponding weighting factors applied during testing as defined by the ISO 8178 D2 standard. Key performance metrics, including torque, speed, and exhaust emissions, were recorded during the tests. This rigorous testing methodology ensured accurate data collection, providing insight into the performance and compliance with emission regulations.

Table 3.2 Weighting factors of ISO 8178 D2 Test Cycle for non-road diesel engine application

Mode number	1	2	3	4	5
Torque (%)	100	75	50	25	10
Weighting factors	0.05	0.25	0.30	0.30	0.10

3.3.2 Design of Experiment

The experiment was conducted under steady-state conditions, which were achieved when the intake manifold temperature exceeded 40°C. During the testing, the engine speeds were maintained at 2000 ± 30 rpm and 2500 ± 30 rpm to ensure consistency. To prevent coke formation, the fuel return temperature after the cooler was kept as close as possible to the fuel inlet temperature. The tests included B0, alongside blends of B10, HDPE10, and PP10 as the tested fuels. The testing followed the ISO 8178 D2 protocol, which is specifically designed for steady-state engine testing and exhaust emission measurements in constant-speed and non-road diesel engines. The weighting factors, torque load, engine speed, and corresponding power levels used in this research are detailed in Table 3.2. Low loads were defined as 10% and 25% of the engine's full load capacity, representing light-duty conditions often encountered during idling or low-speed cruising. The medium load condition was set at 50% which simulates typical mid-range operational demands. High loads corresponding to 75% and 100% reflect heavy-duty conditions, such as acceleration or full-power operation. The start of injection (SOI) timing was controlled by the engine's control unit and kept at its default setting throughout the tests.

Engine power output was adjusted by varying the torque load, and the engine was allowed to stabilize for 10 minutes once steady-state conditions were reached. After stabilization, emission data were recorded using gas analysers for 30 seconds and repeated 3 times. This procedure adhered to international standards for exhaust emission monitoring as outlined by Byshov *et al.* (2018) and Yamanishi *et al.* (2018). The recorded data from each repetition were then averaged to produce a single representative data point. For the modelling phase, all averaged data points from various engine speeds and loads were compiled, resulting in a total of 900 data points for each fuel sample. These comprehensive datasets were then used as input for training and testing the predictive models. The standard Yanmar diesel engine test cycle used in this research corresponded to the Type D2 category, which operates at constant speed. The ISO 8178 D2 test cycle calculates the weighted average exhaust emission values based on the rated engine speed, ensuring compliance with emission regulations. To maintain accuracy, filter papers were replaced between each parameter

test to eliminate cross-contamination from residual exhaust emissions trapped during the previous test.

3.4 Engine Performance

The DM6 software was utilized during the experiment to measure and record the real-time performance of the engine. The software integrated with the engine dynamometer system enabled continuous monitoring and logging of key variables such as torque, engine speed (rpm), fuel consumption, and temperature readings. Data were captured at regular intervals during each test cycle, ensuring consistency and reliability of the results. The recorded data were automatically stored in a digital format, allowing for post-processing and detailed analysis to compute performance metrics such as brake power (BP), brake-specific fuel consumption (BSFC), and brake thermal efficiency (BTE).

A key metric analysed was BP, which was calculated using the logged torque and rpm values as described in Equation 3.1. BP reflects the engine's usable power output, excluding losses to auxiliary systems like fuelling, lubrication, cooling, and emission controls. This measurement provides a realistic assessment of the engine's performance capabilities under actual operating conditions.

$$BP = \frac{2\pi NT}{60 \times 1000} (kW) \quad (\text{Eq. 3.1})$$

Where N is the number of rpm and T is the torque (Nm).

BSFC evaluates the efficiency with which the engine converts fuel into power. It is calculated by dividing the fuel consumption rate by the brake power, as shown in Equation 3.2. Lower BSFC values indicate better fuel efficiency, which is essential for optimizing performance and reducing operational costs.

$$BSFC = \frac{\text{Fuel flow (g/hr)}}{\text{brake power}} \text{ (g/kWh)} \quad (\text{Eq. 3.2})$$

BTE is a critical parameter that measures the efficiency of fuel energy conversion into useful work. It compares the brake power output to the total energy input provided by the fuel, factoring in its calorific value as shown in Equation 3.3. Higher BTE values signify improved energy utilization, contributing to better engine performance and reduced greenhouse gas emissions.

$$BTE = \frac{BP \times 3600 \times 100}{\text{Fuel flow} \times \text{Cal.Value}} (\%) \quad (\text{Eq. 3.3})$$

The combination of automated data logging through DM6 software and calculated performance parameters provided a comprehensive and accurate evaluation of engine behaviour under different fuel blends and load conditions.

3.5 Emissions Measurement

Figure 3.12 depicts the SPTC Autochek GP-20G gas analyser, which was used to measure exhaust emissions during engine testing. This device plays an important role in accurately detecting and quantifying key pollutants for assessing engine performance. The SPTC Autochek GP-20G is equipped with advanced sensor technology that provides precise measurements under dynamic engine conditions. It allows for continuous and real-time monitoring of exhaust emissions. Table 3.3 outlines the key performance characteristics of the SPTC Autochek GP-20G, including its detection range, accuracy, and response time. These specifications ensure the analyser delivers reliable and consistent data throughout the testing process. The use of the analyser is important for gathering accurate emission data for optimizing engine operation to reduce harmful emissions.



Figure 3.12 SPTC Autochek GP-20G gas analyser

Table 3.3: Performance of SPTC Autochek GP-20G gas analyser

Measurement method	HC, CO, C ₂ : Non-dispersive Infrared (NDIR) Measurement O ₂ , NO _x : Electrochemical cell
Measuring range	HC : 0 ~ 10,000 ppm CO : 0 ~ 10% CO ₂ : 0 ~ 20% O ₂ : 0 ~ 25% NO _x : 0 ~ 5,000 ppm
Resolution	HC, NO _x : 1 ppm CO, CO ₂ , O ₂ : 0.01%
Accuracy	CO : 0.00 – 10.00% (±0.02%) HC : 0 – 2,000 ppm (±4 ppm) CO ₂ : 0.00 – 16.00% (±0.3%) O ₂ : 0.00 – 25.00% (±0.01%)

Ağbulut *et al.* (2019) and Pilusa *et al.* (2012) summarized the basic conversion from exhaust gas emission (ppm and vol%) to BSFC (g/kWh) from Equations 3.4 to 3.8.

$$\text{CO (g/kWh)} = 3.591 \times 10^{-3} \times \text{CO (ppm)} \quad (\text{Eq. 3.4})$$

$$\text{CO}_2 \text{ (g/kWh)} = 63.47 \times \text{CO}_2 \text{ (vol \%)} \quad (\text{Eq. 3.5})$$

$$\text{HC (g/kWh)} = 2.002 \times 10^{-3} \times \text{HC (ppm)} \quad (\text{Eq. 3.6})$$

$$\text{NO}_x \text{ (g/kWh)} = 6.636 \times 10^{-3} \times \text{NO}_x \text{ (ppm)} \quad (\text{Eq. 3.7})$$

$$\text{O}_2 \text{ (g/kWh)} = 41.024 \times \text{O}_2 \text{ (vol \%)} \quad (\text{Eq. 3.8})$$

3.6 Model Development

The MLP model is a powerful tool within the realm of ANN, providing a structured approach for model building and training. This process enables the MLP to effectively identify complex patterns within datasets. During the training phase, input data passes through multiple layers of neurons, each layer progressively refining the model's ability to recognize and learn intricate relationships between the variables. As training progresses, the model's structure evolves, adjusting weights and biases in response to the patterns identified within the data. The more detailed the training process, the more refined the model becomes, with its layers evolving to handle increasingly complex and non-linear relationships. This is particularly useful for predicting outcomes where traditional linear models may fall short. In the case of diesel engine emissions, the primary goal is to accurately replicate the combustion process's complex dynamics and predict specific emissions based on various input parameters.

Figure 3.13 provides a flowchart illustrating the process of developing non-linear models specifically for forecasting emissions from a diesel engine during combustion. It outlines the essential steps involved in training the MLP model, such as data preprocessing, model optimization, and validation. Through this continuous iterative process, the MLP model becomes a reliable tool for emission prediction, providing valuable insights into the environmental effects of different fuel blends and engine operating conditions.

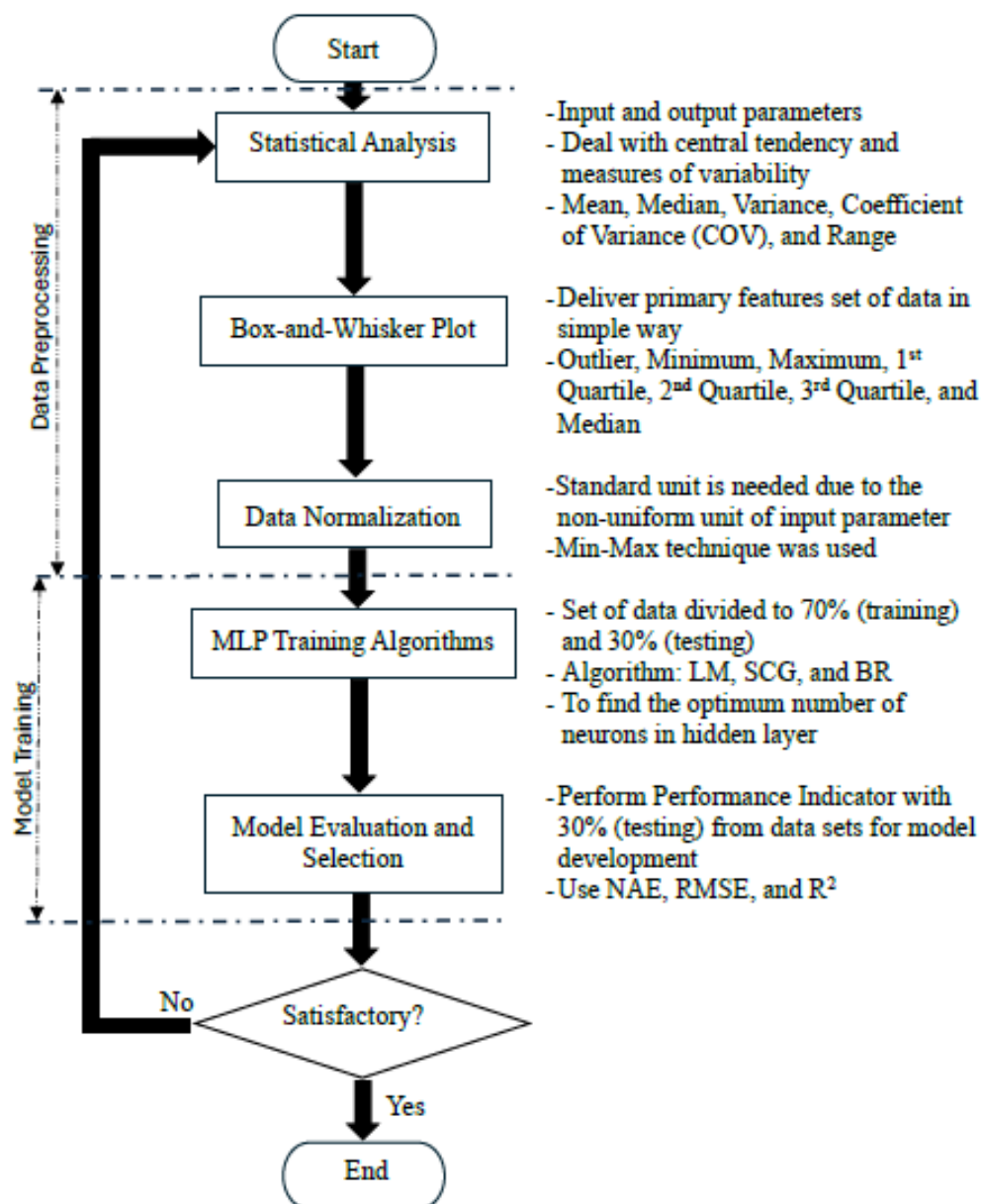


Figure 3.13 Flowchart for developing and forecasting specific emissions from a diesel engine

3.6.1 Box-and-Whisker Plot

Boxplots are an important tool for visualizing the distribution of data and have been effectively employed in several studies by Abdullah *et al.* (2016) and Ismail *et al.* (2016) to summarize and define statistical properties of datasets. A boxplot provides a clear and intuitive graphical representation that highlights key features of the data distribution. The central bar represents the median (or the 50th percentile, Q2) of the data that divides the data into two halves. The interquartile range (IQR), shown as the box itself, spans from the 25th percentile (Q1) to the 75th percentile (Q3) and captures the middle 50% of the data. This range highlights the variability and spread of the data within this central portion.

The whiskers of the boxplot extend from the box to indicate the minimum and maximum values within a defined range, excluding outliers. Data points that lie beyond these whiskers are considered outliers and are typically marked separately, helping to identify extreme values that may need further investigation. Figure 3.14 illustrates how the boxplot effectively encodes key statistical properties such as the median, quartiles, and overall range of a variable. By providing a clear visual summary of the data distribution, boxplots not only reveal the central tendency and spread of the data but also highlight the presence of outliers and the overall shape of the distribution. The vertical scale generally spans from the minimum to the maximum value of the selected dataset, presenting a comprehensive view of the data spread and making it easy to compare multiple datasets or groups.

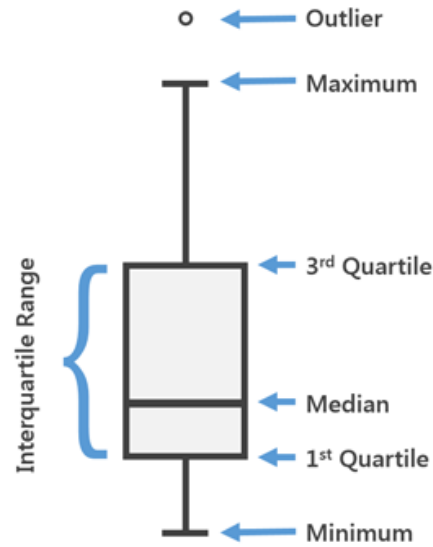


Figure 3.14 Characteristic of Box-and-Whisker plot (Mouli *et al.*, 2024)

3.6.2 Statistical Analysis

Statistical distribution measures are used to analyse data by focusing on two key components: central tendency and variability. Central tendency refers to summary statistics that represent the center or typical value of a dataset, such as the mean and median. The measures of variability provide an understanding of the spread or dispersion of the data and indicators like standard deviation, variance, range, and minimum and maximum values. A box-and-whisker plot is used to visually represent the distribution trends of exhaust emission concentrations measured during the experimental process. Previous studies have emphasized the importance of considering both central tendency and variability as the first step in data analysis (Ismail *et al.*, 2016; Shaziayani *et al.*, 2022; Stoyanov *et al.*, 2023). By using these statistical measures, the data can be summarized in a way that provides a clear understanding of its characteristics and patterns. The data is represented as a series of observations: $x_1, x_2, x_3, \dots, x_n$, where n is the number of observations. The statistical measures of each dataset, such as the mean, median, and variability indicators, were calculated using Microsoft Excel 2019. These calculations allow for a comprehensive understanding of the data distribution and serve as the basis for further analysis. A

summarized formula for evaluating these statistical distribution indicators is provided by Joy *et al.* (2022) and Meerasri & Sothornvit (2022).

To analyse the data, the first step is to arrange the dataset in ascending order, from the lowest value. x_1 to the highest value x_n . The minimum value is the first data point, x_1 , and the maximum value is the last data point, x_n , as shown in Equations 3.9 and 3.10, respectively. The range of the dataset is determined by calculating the difference between the maximum and minimum values as expressed in Equation 3.11. This provides an understanding of how spread out the data points are. The sum of the dataset, as shown in Equation 3.12, is simply the total of all data points, offering a high-level overview of the magnitude of the dataset. The mean represents the central value of the dataset. It is calculated by dividing the sum of all values by the total number of observations, as shown in Equation 3.13. The mean is widely used to summarize the general trend of the data. The median is another key measure of central tendency, which represents the middle value when the data is ordered from lowest to highest. If the dataset contains an odd number of observations, the median is the middle value. If the dataset has an even number of observations, the median is the average of the two middle values, as shown in Equations 3.14 and 3.15.

The standard deviation is a key measure of the spread of data points around the mean, calculated as the square root of the variance (σ) as shown in Equation 3.16. It is often preferred over variance because it is expressed in the same units as the original data, making it more intuitive for interpreting the degree of variation. The variance (σ^2) derived using the method of moments estimator quantifies the dispersion of the dataset by measuring how much each data point deviates from the mean, as depicted in Equation 3.17. While it provides insight into variability, variance is expressed in squared units, which can be less easily interpreted compared to the standard deviation. The mid-range (MR) offers a quick estimate of central tendency, calculated as the arithmetic mean of the maximum and minimum values in the dataset, as shown in Equation 3.18. It provides a simple overview of the central value when more sophisticated measures are not required. The interquartile range (IQR) measures the spread of the middle 50% of the data, defined as the difference between Q1 and Q3 as discussed in the Box-and-Whisker plot section and represented in Equation 3.19. The

IQR is particularly useful for understanding the variability within the central portion of the dataset and reducing the influence of extreme values. Outliers are data points that fall significantly outside the normal range and can skew statistical interpretations. They are identified as values that lie beyond the upper fence or lower fence, calculated using the IQR as shown in Equations 3.20 and 3.21. Identifying outliers helps to ensure that the data analysis is not unduly influenced by extreme values. Lastly, the coefficient of variation (CV) or relative standard deviation is a useful metric for comparing the variability of different datasets, especially when the datasets have different units or scales. The CV is calculated as the ratio of the standard deviation to the mean, as shown in Equation 3.22. Expressed as a percentage, it helps to assess the relative variability of the data about its mean, providing an intuitive way to compare datasets with differing units or magnitudes.

$$\text{Minimum, Min} = x_1 = \min(x_i) \sum_{i=1}^n x_1 \quad (\text{Eq. 3.9})$$

$$\text{Maximum, Max} = x_n = \max(x_i) \sum_{i=1}^n x_n \quad (\text{Eq. 3.10})$$

$$\text{Range} = x_n - x_i \quad (\text{Eq. 3.11})$$

$$\text{Sum} = \sum_{i=1}^n x_i \quad (\text{Eq. 3.12})$$

$$\text{Mean, } \bar{x} = \frac{\sum_{i=1}^n x_i}{n} \quad (\text{Eq. 3.13})$$

$$\text{Median} = x_{\left(\frac{n+1}{2}\right)} \text{ if } n \text{ is odd} \quad (\text{Eq. 3.14})$$

$$\text{Median} = \frac{x_{\left(\frac{n}{2}\right)} + x_{\left(\frac{n}{2} + 1\right)}}{2} \text{ if } n \text{ is even} \quad (\text{Eq. 3.15})$$

$$\text{Standard Deviation, } \sigma = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}} \quad (\text{Eq. 3.16})$$

$$\text{Variance, } \sigma^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1} \quad (\text{Eq. 3.17})$$

$$\text{Midrange, MR} = \frac{x_{\min} + x_{\max}}{2} \quad (\text{Eq. 3.18})$$

$$\text{Interquartile range, } IQR = Q_3 - Q_1 \quad (\text{Eq 3.19})$$

$$\text{Outliers: 1. Upper fence} = Q_3 + (1.5 \times IQR) \quad (\text{Eq 3.20})$$

$$2. \text{ Lower fence} = Q_1 - (1.5 \times IQR) \quad (\text{Eq 3.21})$$

$$\text{Coefficient of Variation, } CV = \frac{\sigma}{\bar{x}} \quad (\text{Eq. 3.22})$$

Where $x_i = i^{th}$ observation and n = number of data samples

3.7 Data Normalization

The data for both dependent and independent variables are measured in different units, necessitating the normalization of the data for consistency and comparability. Data normalization scales the values into a standardized range between 0 and 1, ensuring that all variables are treated equally regardless of their original units (Djordjević *et al.*, 2022; Wang & Tang, 2015). The min-max normalization technique is applied as described by Equation 3.23. This method transforms each data point by subtracting the minimum value of the dataset and dividing it by the range, the difference between the maximum and minimum values. The advantage of the min-max technique is that it retains the relative relationships among the data points, without introducing any distortion or bias into the data. Normalizing the data ensures that all variables contribute equally to the analysis, preventing variables with larger numerical scales from dominating the model. This normalization process is often accompanied by a transformation that may include techniques such as scaling or adjusting data distributions, as referenced by previous studies (Djordjević *et al.*, 2022; Meerasri & Sothornvit, 2022; Wang & Tang, 2015).

$$Z_i = \frac{x_i - (x_{min})}{(x_{max}) - (x_{min})} \quad (\text{Eq. 3.23})$$

Where $x = (x_1, \dots, x_n)$ and Z_i is the i^{th} normalized data

3.8 Types of Training Algorithms for Multilayer Perceptron Models

Several parameters were considered as inputs for the model, including load (at 10%, 25%, 50%, 75%, and 100%), engine speed (2000 rpm and 2500 rpm), torque, power, BSFC, and emissions. These input parameters are fed into the MLP network, which then executes output predictions for NO_x emissions. The dataset was split into two parts: 70% was used for training the model, and the remaining 30% was reserved for testing the model's performance (Nguyen *et al.*, 2021; Vrigazova, 2021). A common guideline suggests using 18 neurons in the hidden layer, as it should not exceed twice the 9th number of input parameters (Deng, 2023). Nevertheless, increasing this slightly to 19 neurons helps the model capture more complex patterns without being too restrictive. Testing with 19 neurons helps find the right balance between accuracy and generalization. Too few neurons cause underfitting, while too many neurons can lead to overfitting, causing the model to fail to learn important relationships in NO_x emissions.

To determine the optimal number of neurons in the hidden layer, a trial-and-error approach was employed. This method involves testing different configurations to find the one that produces the best results. For model training, the learning rate was set at 0.05 to enhance the performance and optimization of the MLP network. The model was trained for 1000 epochs, and the process was repeated 10 times, all results were recorded. From these runs, the model with the highest R² and lowest RMSE was selected. In this work, the best-performing model configuration was chosen. The model with the highest R² and lowest RMSE was selected as the final representative model. This approach was chosen to ensure that the model with the most accurate and reliable prediction capability, capturing the optimal performance, was identified and highlighted. Averaging the values could potentially dilute the performance of this best-case scenario, especially when the differences between runs are small. By selecting the model with the best R² and lowest RMSE, the results truly represent the highest achievable performance of the model under the given conditions. This approach ensures that the best-performing model configuration is captured, reflecting the most accurate and reliable prediction capability. All training and testing algorithms were implemented in MATLAB R2024b. Figure 3.15 illustrates the architecture of the neural network, which consists of three distinct layers: the input layer, the hidden layer,

and the output layer. This structure allows the model to process the input data and learn from it to predict NO_x emissions effectively.

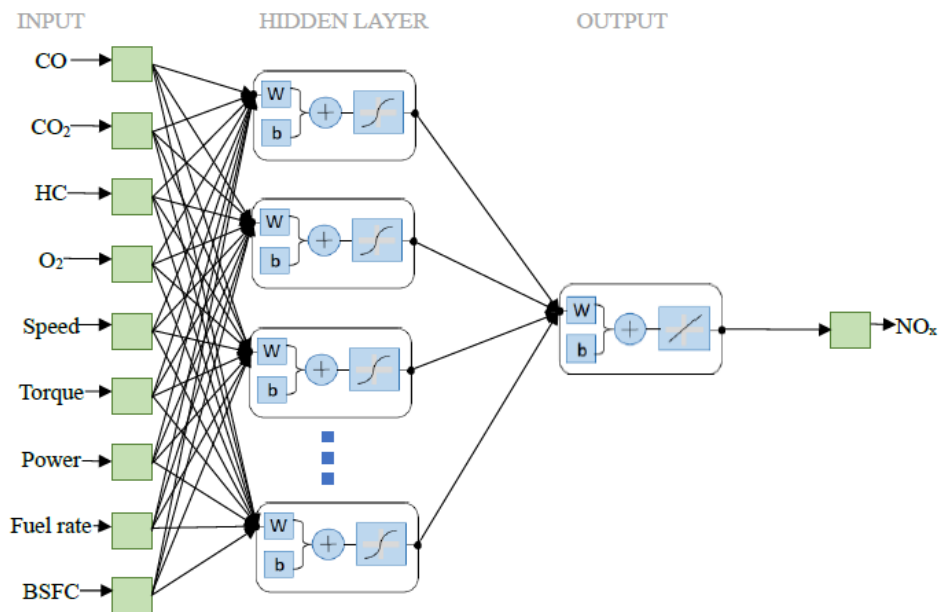


Figure 3.15 Architecture of the neural network model

ANN offers a compelling alternative to traditional mathematical methods, providing numerous benefits for solving complex problems. It is highly adaptive and able to adjust to changing environments, manage incomplete data, make decisions under uncertainty, and tolerate errors. These features make ANN particularly well-suited for tasks such as classification, pattern recognition, signal processing, data compression, and optimization. The versatility of ANN has been proven in a wide range of applications, including data mining, optical character recognition, route optimization, fingerprint identification, material analysis, job scheduling, quality control, and medical diagnostics (Kumari *et al.*, 2021; Hoang *et al.*, 2021). Several neural network algorithms were utilized, including the LM, SCG, and BR. These algorithms were selected for their efficiency in training neural networks and their ability to deliver accurate predictions from complex datasets.

3.8.1 Levenberg-Marquardt Training Algorithm

The Hessian matrix is not required when using the LM back propagation technique, which was designed to use the second-order training method. The sum of squares can be used to express the performance function (Bernal *et al.*, 2019; Lillicrap *et al.*, 2020). As a result, it is possible to determine the gradient and the Hessian matrix approaches:

$$H = M^T \cdot M \quad (\text{Eq. 3.24})$$

$$g = M^T \cdot e \quad (\text{Eq. 3.25})$$

Where M is the Jacobian matrix that contains the first-order derivatives of network errors based on weights and biases, and turns into a vector of network failures. The Jacobian matrix can be computed more quickly than the Hessian matrix by using the traditional back-propagation approach. The LM algorithm uses this approximation to the Hessian matrix in the Newton-like Eq. 3.26.

$$x_{k+1} = x_k - |M^T M + \rho I|^{-1} M^T e \quad (\text{Eq. 3.26})$$

Where x = Weight of neural networks

M = Jacobian matrix of the performance criteria to be minimized

ρ = Scalar that controls the learning process

e = The residual error factor

When ρ is set to zero, the Hessian matrix used for approximation will be used. When ρ is large, this becomes gradient descent with a small step size. Newton's method is quicker and more accurate when trying to get the least number of mistakes, so the aim is to shift toward Newton's method as quickly as possible. Thus, ρ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step increases the performance function. This algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks up to several hundred weights. It also has an efficient implementation in MATLAB® software because the solution of the matrix equation is a built-in

function, so its attributes become even more pronounced in a MATLAB environment. As a result, the performance function is always reduced at each iteration of the algorithm. It might be claimed that the LM technique is more powerful compared to gradient descent (Gukov *et al.*, 2024).

3.8.2 Scale Conjugate Gradient Training Algorithm

Weights in a basic algorithm govern the gradient's most negative and steepest descent direction. The performance function is declining most rapidly in this direction. Even though the function declines the quickest along with the negative of the gradient, this does not produce the fastest convergence (Benbaki *et al.*, 2023). The error minimization achieved in all earlier steps is preserved by conjugate gradient techniques. In this situation, a search is typically conducted along the route that produces convergence more quickly than one of the steepest descents (Lavington *et al.*, 2023). This direction is known as the conjugate direction. There is usually an SCG algorithm that allows control of the step size at each iteration. The performance function is minimized throughout the step-size determination procedure, which is done along the SCG direction. The primary feature of the SCG algorithms is that they begin their initial search in the direction of the steepest descent, as shown in Equation 3.27 (Benbaki *et al.*, 2023). Equations 3.28 and 3.29 represent the SCG techniques that are widely used in inline search.

$$p_0 = -g_0 \quad (\text{Eq. 3.27})$$

$$x_{k+1} = x_k + \alpha_k g_k \quad (\text{Eq. 3.28})$$

$$p_k = g_k + \beta_k p_{k-1} \quad (\text{Eq. 3.29})$$

SCG techniques can be distinguished based on how the factor β_k is computed. Aside from the line search method, there are other methods for calculating step size. SCG can be combined with the model trust region approach, which is well-known from the LM algorithm, to develop a new method (Lavington *et al.*, 2023). The brand-new method is known as SCG, as shown in Equation 3.30.

$$s_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k} + \lambda_k p_k \quad (\text{Eq. 3.30})$$

In this approach, the user starts the process with scaling factors. λ_k and σ_k Set to values of $0 < \lambda_k < 10^{-6}$ and $0 < \sigma_k < 10^{-4}$, where s is the Hessian matrix approximation. E is the total error function, and E' is the gradient of E . The factor β_k Computation and new search directions for the SCG are as in Equations 3.31 and 3.32. It is crucial to update the design parameters independently for each user iteration of the algorithm to succeed. Given the functionality of line search-based algorithms, this is a significant advantage.

$$\beta_k = \frac{(|g_{k+1}|^2 - g_{k+1}^T g_k)}{g_k^T g_k} \quad (\text{Eq. 3.31})$$

$$p_k = g_{k+1} + \beta_k p_k \quad (\text{Eq. 3.32})$$

3.8.3 Bayesian Regularisation Training Algorithm

A training algorithm where weight and bias values are updated is the BR algorithm, according to the LM algorithm. To create a network that can be most effectively generalized, BR first minimizes the composition of weights and squared errors before identifying an exact composition (Thomas & Suhner, 2015). Network weights are incorporated via BR into the second-order training objective function, denoted as $F(\omega)$ in Equation 2.25.

$$F(\omega) = \alpha E_\omega + \beta E_D \quad (\text{Eq. 3.33})$$

In Equation 2.25, E_ω represents the sum of the squared network weights and E_D is the sum of network errors with objective function parameters denoted by α and β . The network weights are treated as random variables in the BR framework, and the distribution of the network weights and the training set is regarded as a Gaussian distribution. The Bayes theorem is used to define the α and β factors. According to

their prior probability and posterior or conditional probabilities, variables A and B are related by the Bayes theorem in Equation 3.34 (Sun *et al.*, 2023).

$$P(A|B) = \frac{P(A|B) P(A)}{P(B)} \quad (\text{Eq. 3.34})$$

Where $P(A|B)$ is the posterior probability of A given that B exists, $P(A|B)$ denotes the prior probability of B given that A exists, and $P(B)$ denotes the non-zero prior probability of event B, which serves as a normalizing constant. Equation 3.35, which is similar to maximizing the posterior probability function given in Equation 2.27, needs to be minimized to discover the ideal weight space.

$$P(\alpha, \beta | D, M) = \frac{P(D | \alpha, \beta, M) P(\alpha, \beta | M)}{P(D|M)} \quad (\text{Eq. 3.35})$$

Where α and β = optimized factors

D = weight distribution

M = particular neural network architecture

$P(D | M)$ = normalization factors

$P(\alpha, \beta | M)$ = uniform prior density for the regularization parameters

$P(D | \alpha, \beta, M)$ = function of D for given α, β, M

As a result, optimum values for α and β for a given weight space are found. The algorithm then enters the LM phase to compute the Hessian matrix and updates the weight space to minimize the objective function. When convergence is not achieved, the algorithm estimates fresh values and repeats the process until convergence is achieved (Khan & Rue, 2021).

3.9 Validation Model through Performance Indicators

Three performance indicators (PI) were utilized to assess the accuracy and fit of the models. These indicators help determine the effectiveness of the model by

evaluating both its accuracy and error. Specifically, the accuracy measure is considered optimal when its value approaches 1, while the error measure is best when the value is closer to 0 (Chicco *et al.*, 2021; López *et al.*, 2022). RMSE measures the average magnitude of the errors between predicted and observed values. It is particularly sensitive to large errors, so lower values indicate a better model performance, reflecting smaller discrepancies between the predicted and actual data as represented in Equation 3.36. Normalized Absolute Error (NAE) is a normalized version of the absolute error scaled by the range of the observed data. This makes it useful for comparing models across different datasets or scales, for a clear measure of error relative to the spread of the data represented in Equation 3.37. R² value indicates how well the model's predictions match the actual observed values. An R² value closer to 1 suggests that the model explains most of the variance in the data, while a value near 0 indicates poor model fit and minimal explanatory power represented by Equation 3.38. These indicators were key in evaluating and comparing the models, helping to identify the one that best predicts the NO_x emissions during engine operation.

$$\text{RMSE} = \left(\frac{1}{n} \sum_{i=1}^n [P_i - O_i]^2 \right)^{\frac{1}{2}} \quad (\text{Eq. 3.36})$$

$$\text{NAE} = \frac{\sum_{i=1}^n |P_i - O_i|}{\sum_{i=1}^n O_i} \quad (\text{Eq. 3.37})$$

$$R^2 = \left(\frac{\sum_{i=1}^n (P_i - \underline{P})(O_i - \underline{O})}{n \cdot S_{pred} \cdot S_{obs}} \right)^2 \quad (\text{Eq. 3.38})$$

Where n = total number of data

P_i = predicted values

O_i = observed values

P = mean of predicted values

O = mean of observed values

S_{pread} = standard deviation of predicted values

S_{obs} = standard deviation of the observed values

CHAPTER 4

RESULTS AND DISCUSSIONS

This results and discussion section provides a comprehensive analysis of the experimental findings. The section focuses on assessing the impact of plastic-derived diesel fuels on diesel engine performance, combustion characteristics, and emissions. It begins by characterizing the fuel properties of plastic-derived diesel using FTIR, bomb calorimeter, kinematic viscosity measurement, GCFID, and CHNS elemental analysis. The comparative analysis includes performance and emissions evaluations of diesel engines fuelled with 10% blended with plastic-derived diesel, pure diesel, and palm oil methyl ester biodiesel. This section also presents the training and testing of non-linear predictive models for NO_x emissions using an MLP. The performance of these predictive models is evaluated based on statistical performance indicators. The results offer important new information about the efficiency and environmental effects of using diesel fuels derived from plastic in diesel engines.

4.1 Fuel Properties of Diesel Blends

To characterize the fundamental fuel properties of the diesel blend used, several analytical techniques were employed. FTIR was used to identify functional groups and assess the chemical composition. The calorific value was measured by a bomb calorimeter to determine the energy content. Kinematic viscosity was measured to evaluate flow characteristics for spray atomisation and injection performance. GCFID was employed to analyse the hydrocarbon compositions, while CHNS elemental analysis provided a specific breakdown of the elemental content.

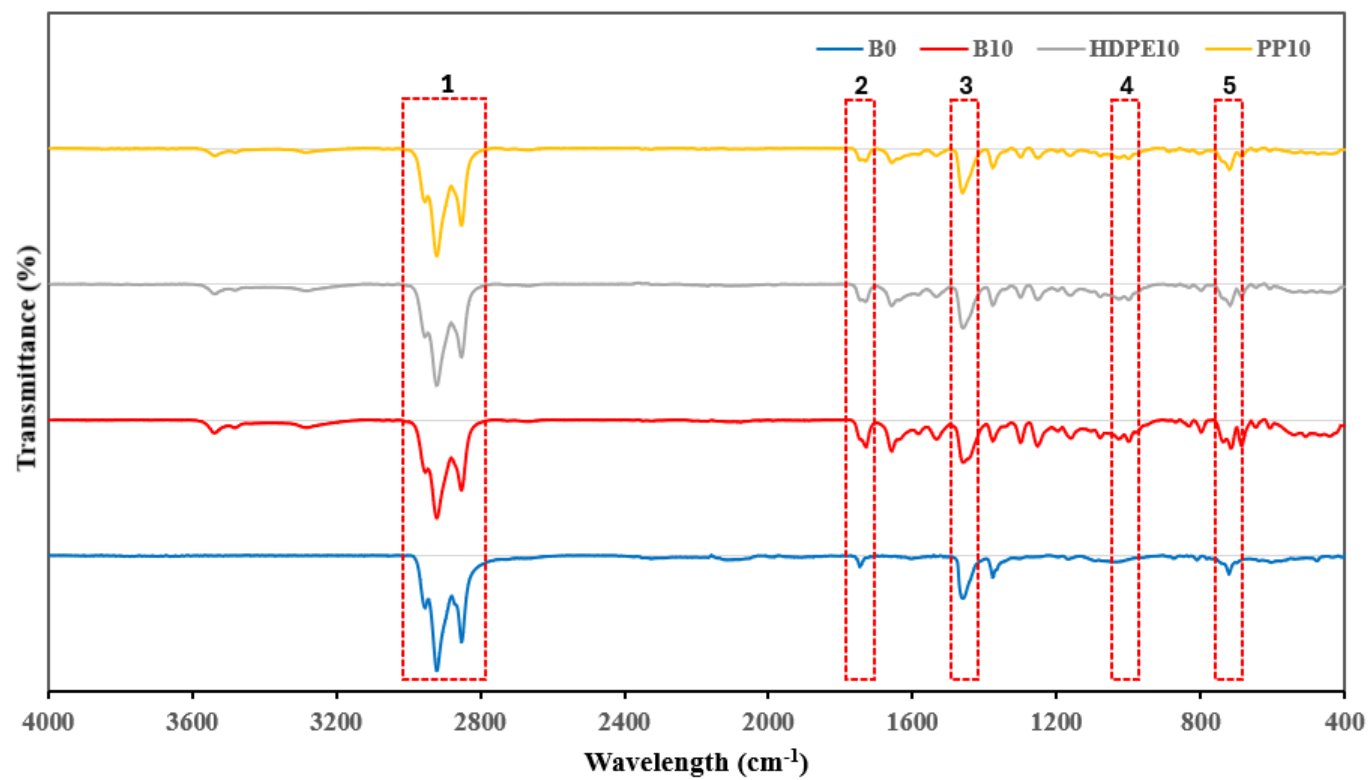
4.1.1 Functional Group

The FTIR spectrum analysis of various blended diesel fuels, including B0, B10, HDPE10, and PP10, is presented in Figure 4.1 and Table 4.1. A prominent absorbance peak was observed within the 2850–3000 cm^{-1} range, corresponding to C–H stretching vibrations of alkanes. This region is associated with $-\text{CH}_2$, $-\text{CH}_3$, and $-\text{CH}$ bonds essential for identifying hydrocarbon chains that define energy content and combustion characteristics. Strong peaks were detected at approximately 2937.72 cm^{-1} , 2922.03 cm^{-1} , and 2853.58 cm^{-1} across all fuel samples. The transmittance at 2922.03 cm^{-1} ranged from 58.11% in B0 to 81.66% in B10, indicating a reduction in hydrocarbon chain density due to the oxygenated nature of biodiesel. These findings are consistent with previous studies by Calero *et al.* (2023), Jiao *et al.* (2021), and Sun *et al.* (2018), which emphasize the importance of alkanes in determining the chemical composition and combustion behaviour of diesel fuels. This suggests a shift toward more complete combustion but with slightly lower volatility and energy content in B10. Higher $-\text{CH}_2$ and $-\text{CH}_3$ content in HDPE10 and PP10 implies retained energy density and combustion stability, though these blends may exhibit slower vaporization and ignition delay compared to conventional diesel.

The FTIR spectra revealed peaks within the 1350–1480 cm^{-1} range corresponding to C–H bending vibrations, confirming the presence of alkane deformations. Strong peaks at 1458.88 cm^{-1} and 1461.73 cm^{-1} with transmittance values between 83.76% and 84.32% were recorded for all samples. C–H rocking vibrations in the 700–725 cm^{-1} range, specifically at 721.59 cm^{-1} , 715.89 cm^{-1} , and

717.32 cm^{-1} exhibited high transmittance values between 89.63% to 93.29%, validating the dominance of aliphatic hydrocarbons. These features are for maintaining thermal stability and flame propagation during combustion, especially for plastic-derived fuels like HDPE10 and PP10. These high transmittance values validate the presence of alkane chains as a dominant structural feature in the fuel samples. The presence of these functional groups aligns with the findings by Calero *et al.* (2023), Ghodke *et al.* (2022), and Jiao *et al.* (2021) highlighted the significance of alkanes in maintaining fuel energy density, thermal stability, and combustion behaviour. The complex peaks in the 400–1500 cm^{-1} fingerprint region for HDPE10 and PP10 suggest the presence of polymer degradation products and branched hydrocarbons, which may lead to irregular ignition delays and varied flame temperatures, potentially affecting combustion efficiency.

Distinct differences were also noted in ester-related regions. B0, as purely petroleum-based, lacked ester peaks, while B10 exhibited strong absorption in the 1735–1750 cm^{-1} region due to C=O stretching vibrations of ester carbonyls. This confirms the biodiesel content in B10 and aligns with improved oxygen availability for combustion. While beneficial for reducing soot, these polar functional groups can raise in-cylinder temperatures and contribute to increased NO_x emissions. Similarly, the same features were observed in HDPE10 and PP10, suggesting the presence of oxygenated species from plastic pyrolysis in low content. The C–O stretching vibrations observed between 1000–1300 cm^{-1} , peaks at 999.68 cm^{-1} and 1002.53 cm^{-1} further support the presence of ester groups in these blends (Faraguna *et al.*, 2019; Hewavitharana *et al.*, 2020). Although these oxygenated compounds improve lubricity and combustion completeness, they can marginally lower the calorific value and increase thermal NO_x formation. The FTIR results show that B10 may offer cleaner combustion with better oxygenation but slightly reduced power output due to its lower hydrocarbon density. In contrast, HDPE10 and PP10 retain high alkane content that supports high energy release with combustion irregularities due to molecular complexity. These insights correlate with performance trends observed in similar studies by Coronado *et al.* (2017), Ghodke *et al.* (2022), and Leng *et al.* (2020), reinforcing the importance of molecular structure in shaping fuel combustion behaviour, thermal efficiency, and emission profiles.



Note: **1.** 2850–3000 cm^{-1} , **2.** 1735–1750, **3.** 1350–1480 cm^{-1} , **4.** 1000–1300 cm^{-1} , and **5.** 700–725 cm^{-1}

Figure 4.1 FTIR graph of the biodiesel blends B0, B10, HDPE10, and PP10

Table 4.1 FTIR spectrum analysis of B0, B10, HDPE10, and PP10

Frequency	Bond type	Functional group	Assignment	Peak (cm ⁻¹)				Transmittance (%)			
				B0	B10	HDPE10	PP10	B0	B10	HDPE10	PP10
2850 - 3000	C-H stretching	alkanes	CH ₂ , CH ₃ , CH (2 or 3 bands)	2937.72	2940.57	2937.72	2937.72	79.44	81.66	78.52	78.25
				2919.18	2922.03	2922.03	2919.18	58.11	63.93	62.69	60.9
				2852.15	2853.58	2853.58	2852.15	68.27	74.22	73.26	71.72
1350 - 1480	C-H bending	alkanes	CH ₂ and CH ₃ deformation	1458.88	1458.88	1458.88	1461.73	84.28	84.32	83.82	83.76
700 - 725	C-H rock	alkanes	CH ₂ rocking	721.59	715.89	717.32	720.17	93.29	89.63	92.26	92.37
1735 - 1750	C=O stretching	esters	C=O	na	1732.68	1729.83	1734.11	na	90.54	93.49	95.61
1000 - 1300	C-O stretching	esters	O-C (2 bands)	na	999.68	1001.11	1002.53	na	92	94.28	96.34

*na = not available

4.1.2 Calorific Value

The calorific value measures a fuel's energy content, indicating its power potential in combustion engines. This study evaluated calorific values to assess energy output and the viability of alternative fuels expressed in MJ/kg. Calculations used a calorimeter's heat capacity and temperature change.

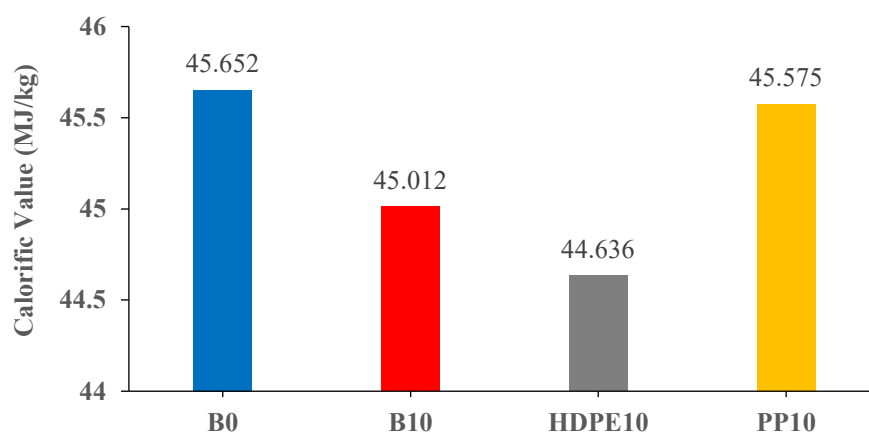


Figure 4.2 Comparison of calorific values for different diesel blends

Figure 4.2 compares the calorific values of different diesel fuel blends, highlighting the energy content variation among B0, B10, HDPE10, and PP10. B0 exhibited the highest calorific value at 45.652 MJ/kg, as the baseline, which is associated with higher energy density. In contrast, the calorific values of B10 (45.012 MJ/kg), HDPE10 (44.636 MJ/kg), and PP10 (45.575 MJ/kg) were slightly lower, reflecting reductions of 1.4%, 2.2%, and 0.2% compared to B0, respectively. These reductions are primarily attributed to the presence of oxygenated compounds in biodiesel and plastic-derived components, which reduced energy density by contributing non-combustible oxygen atoms to the fuel structure (Doppalapudi *et al.*, 2024; Padmanabhan *et al.*, 2022). Despite these reductions, the calorific values of all the blends remain within a narrow range of 0.2% to 2.2% compared to pure diesel, suggesting that these alternative fuels retain a high energy density that is well-suited for efficient combustion in diesel engines. This aligns with findings from Hua (2023) and Kumar *et al.* (2018) reported less than a 10% variation in calorific values for 10%

plastic-derived diesel fuel blends relative to B0. Similarly, Kaisan *et al.* (2020) observed calorific values for 10% plant-based biodiesel blends ranging from 43.25 MJ/kg to 44.06 MJ/kg, representing relatively small reductions when compared to pure diesel with a value of 45.6 MJ/kg.

Among the analysed blends, PP10 with a calorific value of 45.575 MJ/kg is closer to diesel, while HDPE10 with 44.636 MJ/kg has the lowest energy content. This difference is attributed to the chemical composition of the feedstock as PP-derived fuels retain more energy-dense hydrocarbons, while HDPE-derived fuels contain more oxygenated compounds and impurities from the pyrolysis process (Alit *et al.*, 2022; Wu *et al.*, 2024). Some researchers argue that plastic-derived fuels can introduce operational challenges such as higher soot formation and NO_x emissions due to incomplete combustion (Paavani *et al.*, 2024; Yaqoob *et al.*, 2025). However, these issues can be mitigated through refining techniques such as hydrodeoxygenation and the addition of cetane improvers, which enhance combustion characteristics and improve energy output. These minor reductions may slightly influence engine performance and emissions, but their impact on overall combustion efficiency is expected to be negligible.

4.1.3 Kinematic Viscosity

Kinematic viscosity determines the fluid's resistance to flow under the influence of gravity, and it plays a critical role in how effectively fuel is injected into the combustion chamber. The kinematic viscosity of fuel impacts several important aspects of engine performance, such as fuel atomization, combustion efficiency, and lubrication of the engine's internal components. Kinematic viscosity is typically measured in two units: square millimetres per second (mm²/s) and centistokes (cSt). For this research, mm²/s is used as it is the standard unit for assessing the flow characteristics of fuels in diesel engine applications, particularly when evaluating how the fuel interacts with the fuel injection system.

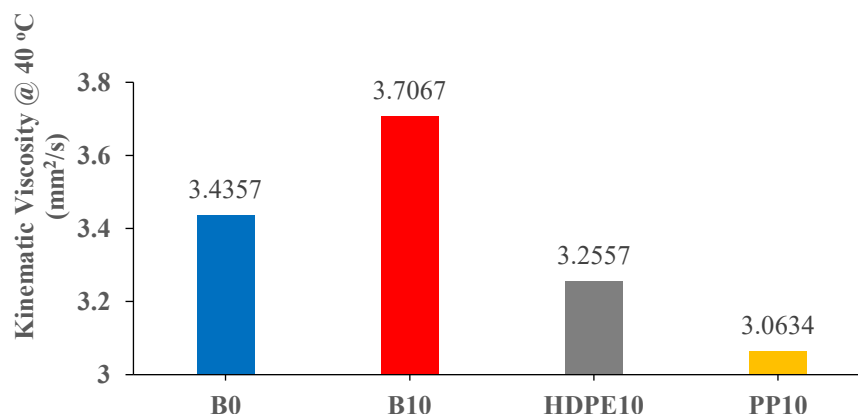


Figure 4.3 Comparison of kinematic viscosity for different diesel fuels

Figure 4.3 presents a comparison of kinematic viscosity for different diesel blends. B0, as the baseline fuel exhibits a kinematic viscosity of 3.4357 mm²/s. Among the blends, B10 displays the highest kinematic viscosity at 3.7067 mm²/s, an increase of 7.9% compared to B0. This increase is primarily attributed to the molecular structure of biodiesel and its oxygenated compounds, which enhance intermolecular interactions and contribute to higher viscosity. Kumar *et al.* (2019) found similar results, with HDPE10 showing a kinematic viscosity of 3.2557 mm²/s, a 5.2% drop compared to B0, while PP10 demonstrates the lowest viscosity at 3.0634 mm²/s, marking a 10.9% decrease. This reduction in viscosity for plastic-derived diesel blends is likely due to the lighter hydrocarbon chains present in these fuels, which reduce resistance to flow (Mustayen *et al.*, 2023). The lower viscosity of HDPE10 and PP10 may offer advantages such as improved atomization and combustion performance, which can enhance engine efficiency and reduce emissions. However, lower viscosity levels may also pose challenges, particularly in the lubrication of fuel injection systems, which rely on adequate viscosity to prevent wear and tear. All diesel blended show values which fall within the standard range specified for diesel fuels between 1.3 mm²/s to 4.1 mm²/s as per ASTM D975-20a and ASTM 7467-20a (Ağbulut *et al.*, 2019; Santos *et al.*, 2021)

4.1.4 Density

Density plays a critical role in determining the energy content of the fuel, atomization during injection, and the AF mixture formation.

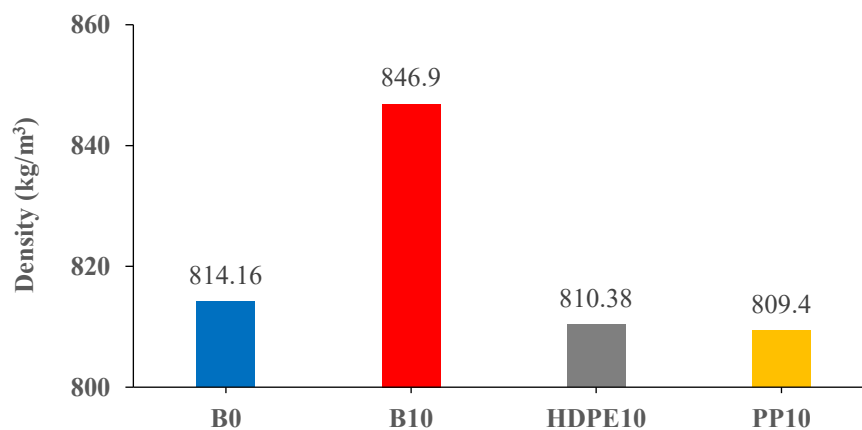


Figure 4.4 Comparison of density for different diesel fuels

Figure 4.4 illustrates the densities of diesel and blended fuels of B0, B10, HDPE10, and PP10 measured at 15°C. B10 exhibits the highest density at 846.9 kg/m³, followed by B0 at 814.16 kg/m³, HDPE10 at 810.38 kg/m³, and PP10 at 809.4 kg/m³. B10 shows a 4.02% increase in density compared to B0, which aligns with the typical characteristics of biodiesel. Higher density in biodiesel is attributed to its oxygenated molecular structure and longer carbon chains (Osman *et al.*, 2024; Yusuf *et al.*, 2024). In contrast, HDPE10 and PP10 show slight reductions in density with decreases of 0.46% and 0.58% compared to B0, respectively. These reductions can be explained by the lighter molecular composition of hydrocarbons derived from plastic pyrolysis (Chang, 2023; Pannucharoenwong *et al.*, 2023). Higher-density fuels such as B10 typically require increased injection pressures to achieve effective atomization. While this can improve AF mixing and combustion efficiency, it may also result in elevated in-cylinder temperatures, potentially contributing to higher NO_x emissions (Huang *et al.*, 2024). Fuels with lower densities, like HDPE10 and PP10, tend to atomize more readily due to their lower resistance to flow. This improved atomization can lead to shorter ignition delays and better combustion efficiency, though it may result in leaner

AF mixtures due to reduced mass flow rates, which could slightly affect engine power output.

The correlation between fuel density and energy content per unit volume is another significant consideration. B10, with its higher density, indicates a marginally greater energy content, which could translate to advantages in torque and power production under similar operating conditions. The higher density may also pose challenges, such as incomplete combustion if atomization is suboptimal and leading to increased HC and CO emissions (Arumugam *et al.*, 2024). In contrast, HDPE10 and PP10 with their lower densities may improve combustion efficiency by facilitating better spray characteristics, but could risk lower energy content, slightly impacting performance in high-load conditions (Liu *et al.*, 2022). The observed differences in density underscore the trade-offs involved in adopting alternative fuel blends. While biodiesel blends like B10 offer advantages in energy density and lubrication, they may require careful management to mitigate higher emissions. Plastic-derived blends such as HDPE10 and PP10 demonstrate potential for enhanced atomization and efficient combustion, but their slightly lower densities necessitate optimization to balance performance, emissions, and engine durability (Jiao *et al.*, 2021).

4.1.5 Hydrocarbon Content

The diesel blends were tested using GC-FID analysis, which focused on the catalytic pyrolysis aids in the identification of present compounds in the sample. Figure 4.5 illustrates the GC-FID compounds list of the standard sample, while Figures 4.6 to 4.9 illustrate the GC-FID compounds list of the various tested diesel blends. The overfitted graph before peak 1 is a hexane solution as a diluter. By comparing the retention duration to the standards, the length distribution of HC was ascertained. Microsoft Excel 365 was used for percentage calculation, while Shimadzu Lab Solution was used to calculate retention time and peak regions. The peak areas of each sample were added to determine the peak area percentages. Tables 4.2 and 4.6 depict the compound list of standard samples and diesel blends by percentages that went

towards the total area in arbitrary units (a.u.) representing the concentration of each compound, respectively.

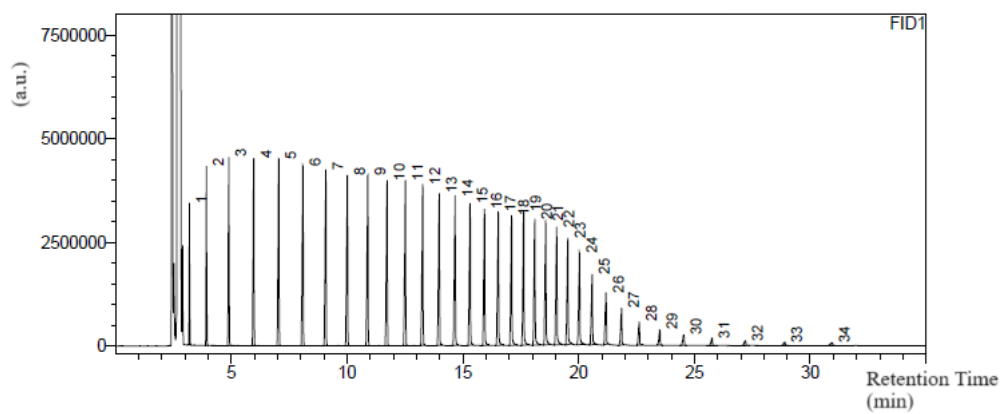


Figure 4.5 GC-FID test for the standard sample

Table 4.2 GC-FID compound list for the standard sample

Peak ID	Retention Time (min)	Area, a.u. (10 ⁵)	Name of the Compound	Chemical Formula
1	3.180	1.1860	Heptane	C ₇ H ₁₆
2	3.902	6.8299	Octane	C ₈ H ₁₈
3	4.859	8.4092	Nonane	C ₉ H ₂₀
4	5.927	37.2650	Decane	C ₁₀ H ₂₂
5	7.013	60.9431	Undecane	C ₁₁ H ₂₄
6	8.081	90.9658	Dodecane	C ₁₂ H ₂₆
7	9.098	162.9828	Tridecane	C ₁₃ H ₂₈
8	10.059	214.7298	Tetradecane	C ₁₄ H ₃₀
9	10.943	224.7666	Pentadecane	C ₁₅ H ₃₂
10	11.767	232.5486	Hexadecane	C ₁₆ H ₃₄
11	12.587	334.5108	Heptadecane	C ₁₇ H ₃₆
12	13.299	138.9280	Octadecane	C ₁₈ H ₃₈
13	14.015	165.4107	Nonadecane	C ₁₉ H ₄₀
14	14.683	136.5595	Eicosane	C ₂₀ H ₄₂
15	15.398	250.2013	Heneicosane	C ₂₁ H ₄₄
16	15.936	102.2300	Docosane	C ₂₂ H ₄₆
17	16.514	92.0500	Tricosane	C ₂₃ H ₄₈
18	17.070	66.4166	Tetracosane	C ₂₄ H ₅₀
19	17.580	53.1764	Pentacosane	C ₂₅ H ₅₂
20	18.048	35.3899	Hexacosane	C ₂₆ H ₅₄
21	18.512	21.4027	Heptacosane	C ₂₇ H ₅₆
22	18.976	9.1496	Octacosane	C ₂₈ H ₅₈
23	19.453	3.8084	Nonacosane	C ₂₉ H ₆₀
24	19.954	0.8804	triacontane	C ₃₀ H ₆₂
25	20.502	0.2372	Hentriacontane	C ₃₁ H ₆₄
26	21.098	0.0907	Dotriacontane	C ₃₂ H ₆₆
27	21.844	0.0140	Tritriacontane	C ₃₃ H ₆₈
28	22.522	-0.0329	Tetratriacontane	C ₃₄ H ₇₀
29	23.436	-0.0195	Pentatriacontane	C ₃₅ H ₇₂
30	24.498	-0.0712	Hexatriacontane	C ₃₆ H ₇₄
31	25.670	-0.0027	Heptatriacontane	C ₃₇ H ₇₆
32	27.007	-0.0415	Octatriacontane	C ₃₈ H ₇₈
33	29.077	0.0118	Nonatriacontane	C ₃₉ H ₈₀
34	30.734	0.0052	Tetracontane	C ₄₀ H ₈₂

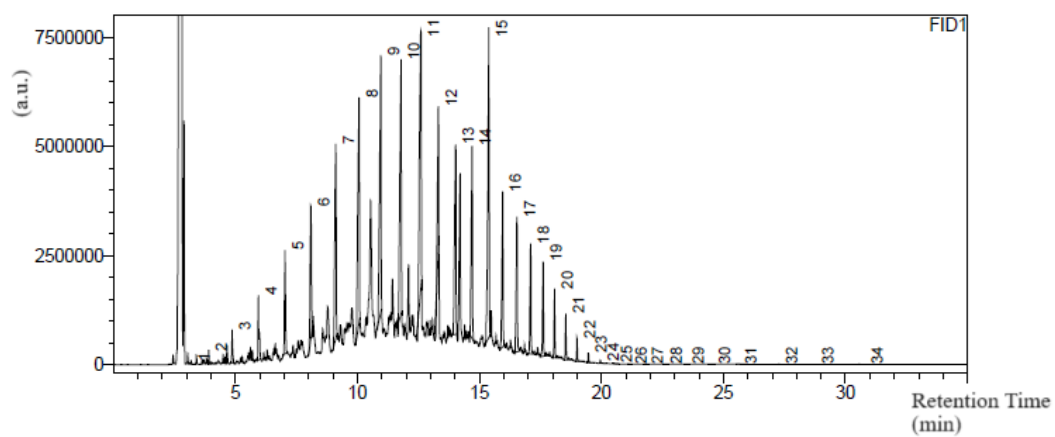


Figure 4.6 GC-FID test for B0

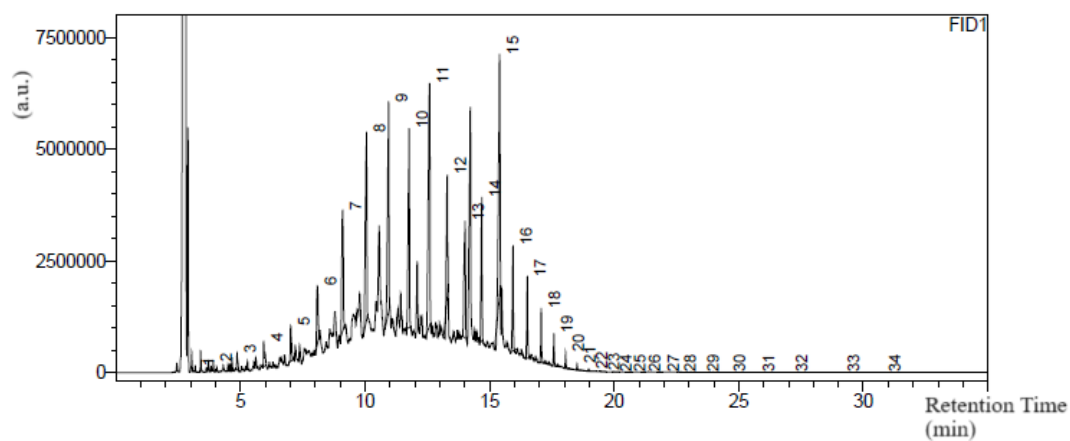


Figure 4.7 GC-FID test for B10

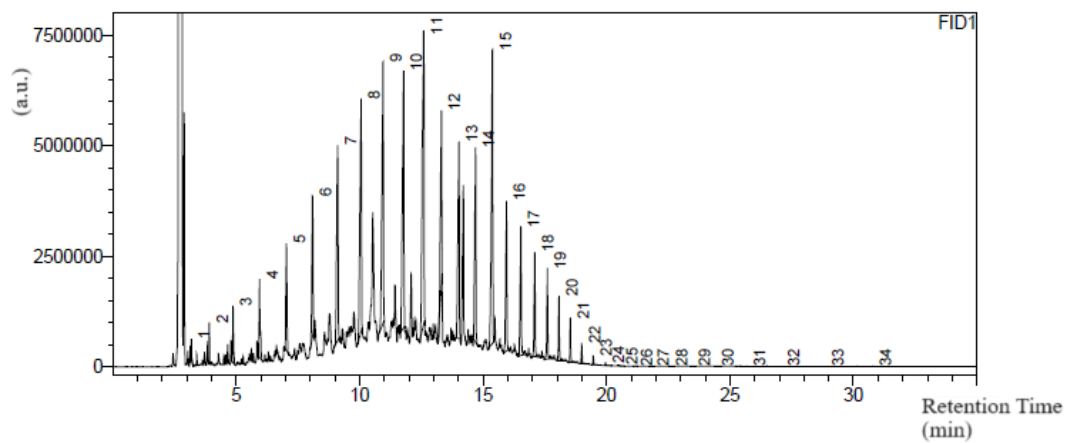


Figure 4.8 GC-FID test for HDPE10

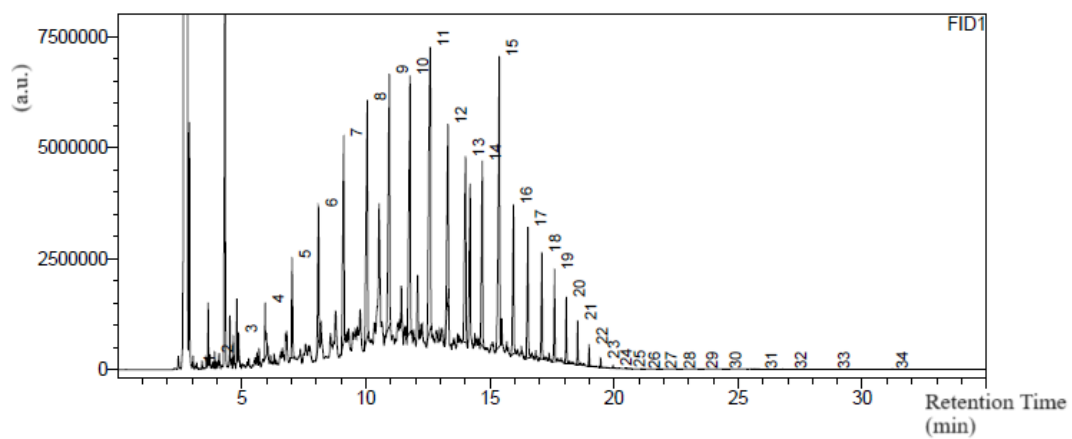


Figure 4.9 GC-FID test for PP10

Table 4.3 GC-FID compound list for B0

Peak ID	Retention Time (min)	Area, a.u. (10 ⁵)	Name of the Compound	Chemical Formula
1	3.181	1.29119	Heptane	C ₇ H ₁₆
2	3.903	5.08045	Octane	C ₈ H ₁₈
3	4.861	16.79945	Nonane	C ₉ H ₂₀
4	5.936	42.52842	Decane	C ₁₀ H ₂₂
5	7.027	67.73314	Undecane	C ₁₁ H ₂₄
6	8.086	103.4921	Dodecane	C ₁₂ H ₂₆
7	9.107	172.8032	Tridecane	C ₁₃ H ₂₈
8	10.066	220.3678	Tetradecane	C ₁₄ H ₃₀
9	10.955	233.5601	Pentadecane	C ₁₅ H ₃₂
10	11.786	229.7193	Hexadecane	C ₁₆ H ₃₄
11	12.598	299.4568	Heptadecane	C ₁₇ H ₃₆
12	13.317	88.74658	Octadecane	C ₁₈ H ₃₈
13	14.026	176.6377	Nonadecane	C ₁₉ H ₄₀
14	14.698	143.7978	Eicosane	C ₂₀ H ₄₂
15	15.383	265.7478	Heneicosane	C ₂₁ H ₄₄
16	15.952	107.7135	Docosane	C ₂₂ H ₄₆
17	16.538	98.14995	Tricosane	C ₂₃ H ₄₈
18	17.098	73.89963	Tetracosane	C ₂₄ H ₅₀
19	17.610	59.07302	Pentacosane	C ₂₅ H ₅₂
20	18.078	37.53817	Hexacosane	C ₂₆ H ₅₄
21	18.539	23.72281	Heptacosane	C ₂₇ H ₅₆
22	18.995	9.98141	Octacosane	C ₂₈ H ₅₈
23	19.464	4.35411	Nonacosane	C ₂₉ H ₆₀
24	19.962	1.00223	triacontane	C ₃₀ H ₆₂
25	20.502	0.31753	Hentriacontane	C ₃₁ H ₆₄
26	21.101	0.11161	Dotriacontane	C ₃₂ H ₆₆
27	21.779	0.04239	Tritriacontane	C ₃₃ H ₆₈
28	22.543	-0.00902	Tetratriacontane	C ₃₄ H ₇₀
29	23.450	0.0184	Pentatriacontane	C ₃₅ H ₇₂
30	24.524	-0.00852	Hexatriacontane	C ₃₆ H ₇₄
31	25.600	0.14399	Heptatriacontane	C ₃₇ H ₇₆
32	27.275	0.03554	Octatriacontane	C ₃₈ H ₇₈
33	28.766	0.03518	Nonatriacontane	C ₃₉ H ₈₀
34	30.769	-0.00153	Tetracontane	C ₄₀ H ₈₂

Table 4.4 GC-FID compound list for B10

Peak ID	Retention Time (min)	Area, a.u. (10 ⁵)	Name of the Compound	Chemical Formula
1	3.180	1.8202	Heptane	C ₇ H ₁₆
2	3.902	3.3876	Octane	C ₈ H ₁₈
3	4.859	10.7449	Nonane	C ₉ H ₂₀
4	5.927	19.0468	Decane	C ₁₀ H ₂₂
5	7.013	25.8372	Undecane	C ₁₁ H ₂₄
6	8.081	50.3843	Dodecane	C ₁₂ H ₂₆
7	9.098	111.3339	Tridecane	C ₁₃ H ₂₈
8	10.059	171.9926	Tetradecane	C ₁₄ H ₃₀
9	10.943	170.2593	Pentadecane	C ₁₅ H ₃₂
10	11.767	151.1571	Hexadecane	C ₁₆ H ₃₄
11	12.587	255.1354	Heptadecane	C ₁₇ H ₃₆
12	13.299	80.1223	Octadecane	C ₁₈ H ₃₈
13	14.015	104.7264	Nonadecane	C ₁₉ H ₄₀
14	14.683	87.3599	Eicosane	C ₂₀ H ₄₂
15	15.398	222.4030	Heneicosane	C ₂₁ H ₄₄
16	15.936	56.7934	Docosane	C ₂₂ H ₄₆
17	16.514	47.8371	Tricosane	C ₂₃ H ₄₈
18	17.070	27.4987	Tetracosane	C ₂₄ H ₅₀
19	17.580	16.3040	Pentacosane	C ₂₅ H ₅₂
20	18.048	7.3392	Hexacosane	C ₂₆ H ₅₄
21	18.512	3.0497	Heptacosane	C ₂₇ H ₅₆
22	18.976	0.9448	Octacosane	C ₂₈ H ₅₈
23	19.453	0.3024	Nonacosane	C ₂₉ H ₆₀
24	19.954	0.0772	triacontane	C ₃₀ H ₆₂
25	20.502	0.0017	Hentriacontane	C ₃₁ H ₆₄
26	21.098	0.0269	Dotriacontane	C ₃₂ H ₆₆
27	21.844	0.0065	Tritriacontane	C ₃₃ H ₆₈
28	22.522	-0.0122	Tetratriacontane	C ₃₄ H ₇₀
29	23.436	0.0036	Pentatriacontane	C ₃₅ H ₇₂
30	24.498	-0.0032	Hexatriacontane	C ₃₆ H ₇₄
31	25.670	0.0054	Heptatriacontane	C ₃₇ H ₇₆
32	27.007	-0.0180	Octatriacontane	C ₃₈ H ₇₈
33	29.077	0.0118	Nonatriacontane	C ₃₉ H ₈₀
34	30.734	-0.0244	Tetracontane	C ₄₀ H ₈₂

Table 4.5 GC-FID compound list for HDPE10

Peak ID	Retention Time (min)	Area, a.u. (10 ⁵)	Name of the Compound	Chemical Formula
1	3.179	1.8063	Heptane	C ₇ H ₁₆
2	3.905	15.0757	Octane	C ₈ H ₁₈
3	4.866	27.5101	Nonane	C ₉ H ₂₀
4	5.940	47.2288	Decane	C ₁₀ H ₂₂
5	7.028	67.8864	Undecane	C ₁₁ H ₂₄
6	8.087	100.0490	Dodecane	C ₁₂ H ₂₆
7	9.104	168.9080	Tridecane	C ₁₃ H ₂₈
8	10.060	219.9486	Tetradecane	C ₁₄ H ₃₀
9	10.948	235.4751	Pentadecane	C ₁₅ H ₃₂
10	11.779	236.6031	Hexadecane	C ₁₆ H ₃₄
11	12.592	331.2184	Heptadecane	C ₁₇ H ₃₆
12	13.312	128.8828	Octadecane	C ₁₈ H ₃₈
13	14.021	169.3427	Nonadecane	C ₁₉ H ₄₀
14	14.692	137.3954	Eicosane	C ₂₀ H ₄₂
15	15.374	245.5838	Heneicosane	C ₂₁ H ₄₄
16	15.947	101.6145	Docosane	C ₂₂ H ₄₆
17	16.533	91.4899	Tricosane	C ₂₃ H ₄₈
18	17.092	65.7526	Tetracosane	C ₂₄ H ₅₀
19	17.606	52.4456	Pentacosane	C ₂₅ H ₅₂
20	18.073	34.7832	Hexacosane	C ₂₆ H ₅₄
21	18.534	20.9002	Heptacosane	C ₂₇ H ₅₆
22	18.992	9.0552	Octacosane	C ₂₈ H ₅₈
23	19.461	3.8470	Nonacosane	C ₂₉ H ₆₀
24	19.958	0.8061	triacontane	C ₃₀ H ₆₂
25	20.499	0.2559	Hentriacontane	C ₃₁ H ₆₄
26	21.099	0.0701	Dotriacontane	C ₃₂ H ₆₆
27	21.772	0.0219	Tritriacontane	C ₃₃ H ₆₈
28	22.522	-0.0332	Tetratriacontane	C ₃₄ H ₇₀
29	23.452	0.0077	Pentatriacontane	C ₃₅ H ₇₂
30	24.392	-0.0021	Hexatriacontane	C ₃₆ H ₇₄
31	25.682	-0.0023	Heptatriacontane	C ₃₇ H ₇₆
32	27.068	0.0019	Octatriacontane	C ₃₈ H ₇₈
33	28.844	-0.0608	Nonatriacontane	C ₃₉ H ₈₀
34	30.786	0.0116	Tetracontane	C ₄₀ H ₈₂

Table 4.6 GC-FID compound list for PP10

Peak ID	Retention Time (min)	Area, a.u. (10 ⁵)	Name of Compound	Chemical Formula
1	3.176	1.1860	Heptane	C ₇ H ₁₆
2	3.902	6.8299	Octane	C ₈ H ₁₈
3	4.865	8.4092	Nonane	C ₉ H ₂₀
4	5.936	37.2650	Decane	C ₁₀ H ₂₂
5	7.025	60.9431	Undecane	C ₁₁ H ₂₄
6	8.086	90.9658	Dodecane	C ₁₂ H ₂₆
7	9.103	162.9828	Tridecane	C ₁₃ H ₂₈
8	10.056	214.7298	Tetradecane	C ₁₄ H ₃₀
9	10.944	224.7666	Pentadecane	C ₁₅ H ₃₂
10	11.775	232.5486	Hexadecane	C ₁₆ H ₃₄
11	12.588	334.5108	Heptadecane	C ₁₇ H ₃₆
12	13.308	138.9280	Octadecane	C ₁₈ H ₃₈
13	14.016	165.4107	Nonadecane	C ₁₉ H ₄₀
14	14.689	136.5595	Eicosane	C ₂₀ H ₄₂
15	15.374	250.2013	Heneicosane	C ₂₁ H ₄₄
16	15.945	102.2300	Docosane	C ₂₂ H ₄₆
17	16.531	92.0500	Tricosane	C ₂₃ H ₄₈
18	17.091	66.4166	Tetracosane	C ₂₄ H ₅₀
19	17.605	53.1764	Pentacosane	C ₂₅ H ₅₂
20	18.073	35.3899	Hexacosane	C ₂₆ H ₅₄
21	18.535	21.4027	Heptacosane	C ₂₇ H ₅₆
22	18.991	9.1496	Octacosane	C ₂₈ H ₅₈
23	19.460	3.8084	Nonacosane	C ₂₉ H ₆₀
24	19.958	0.8804	Triacontane	C ₃₀ H ₆₂
25	20.498	0.2372	Hentriacontane	C ₃₁ H ₆₄
26	21.097	0.0907	Dotriacontane	C ₃₂ H ₆₆
27	21.769	0.0140	Tritriacontane	C ₃₃ H ₆₈
28	22.518	-0.0329	Tetratriacontane	C ₃₄ H ₇₀
29	23.417	-0.0195	Pentatriacontane	C ₃₅ H ₇₂
30	24.370	-0.0712	Hexatriacontane	C ₃₆ H ₇₄
31	25.819	-0.0027	Heptatriacontane	C ₃₇ H ₇₆
32	27.007	-0.0415	Octatriacontane	C ₃₈ H ₇₈
33	28.742	0.0118	Nonatriacontane	C ₃₉ H ₈₀
34	31.089	0.0052	Tetracontane	C ₄₀ H ₈₂

GC-FID was employed to characterize the hydrocarbon composition of four fuel samples, as shown in Figures 4.6 to 4.9, assisted by Table 4.3 until 4.6. The primary objective of this analysis was to quantify and compare the concentration of straight-chain alkanes (n-alkanes) ranging from C7 to C40 and to evaluate the implications of their distributions on fuel combustion properties. The classification of hydrocarbons from C7 to C40 is generally divided into three categories based on their volatility and boiling points. Light hydrocarbons (C7–C12) are primarily associated with gasoline-range fuels, characterized by high volatility and lower boiling points, making them suitable for spark-ignition engines. Medium hydrocarbons (C13–C20) include compounds found in kerosene and diesel fuels, which exhibit moderate volatility and are commonly used in compression-ignition engines. Heavy hydrocarbons (C21–C40) comprise heavier fuel fractions and lubricating oils, possessing higher boiling points and significantly lower volatility (Lucidity, 2021; McCurry, 2018). Retention times of hydrocarbons exhibit a direct correlation with their carbon chain length. Shorter-chain hydrocarbons such as Heptane (C₇H₁₆) and Decane (C₁₀H₂₂) exhibited shorter retention times, while longer-chain hydrocarbons like Tritriacontane (C₃₃H₆₈) and Tetracontane (C₄₀H₈₂) exhibited longer retention times. This pattern is consistent with standard chromatographic principles where longer-chain hydrocarbons experience more resistance and thus move more slowly through the chromatographic column (Liang *et al.*, 2024; Zhang, 2024).

The chromatographic data revealed that the most concentrated compounds in all the diesel blends, with peak areas exceeding 150×10^5 a.u., included Hentriacontane (C₃₁H₆₄), Heptacosane (C₂₇H₅₆), Heptadecane (C₁₇H₃₆), Heptane (C₇H₁₆), Heptatriacontane (C₃₇H₇₆), Hexadecane (C₁₆H₃₄), and Nonacosane (C₂₉H₆₀). These compounds, predominantly n-alkanes of varying chain lengths, are fundamental to the energy content and combustion profile of the fuels. However, B10 exhibited reduced concentrations of Hentriacontane (C₃₁H₆₄) and Hexadecane (C₁₆H₃₄) falling below 150×10^5 a.u. This reduction is likely attributed to the dilution effect caused by the introduction of biodiesel, which typically contains oxygenated compounds such as methyl esters rather than long-chain hydrocarbons. The second most abundant group of hydrocarbons, with peak areas between 100×10^5 a.u. and 150×10^5 a.u., consisted of Heneicosane (C₂₁H₄₄), Hexacosane (C₂₆H₅₄), Hexatriacontane (C₃₆H₇₄), and

Nonadecane ($C_{19}H_{40}$). Among these, Hexacosane ($C_{26}H_{54}$) was less concentrated in B0 and PP10, suggesting a relatively reduced presence of mid- to long-chain alkanes in these blends compared to HDPE10.

The concentration and distribution of hydrocarbons have significant implications for the combustion characteristics of diesel blends. Medium-length alkanes such as Heptatriacontane ($C_{37}H_{76}$) and Nonacosane ($C_{29}H_{60}$) were present in high concentrations, especially in HDPE10 and PP10. These heavy hydrocarbons contribute to higher viscosity and lower volatility, leading to delayed evaporation, extended ignition delay, and the potential for incomplete combustion and soot formation. The lower concentration of long-chain hydrocarbons in B10 reflects the presence of lighter and more oxygenated molecules, which tend to improve fuel atomization and promote complete combustion. This leads to better combustion efficiency and reduced emissions of unburnt hydrocarbons. However, the presence of longer-chain hydrocarbons could potentially contribute to soot formation and increase the PM, which in turn might influence NO_x emissions. This suggests that while these longer-chain hydrocarbons may be part of the mixture, they are not the predominant species (Hwang *et al.*, 2023; Jahirul *et al.*, 2021; Fattah *et al.*, 2020).

The NO_x emissions from diesel engines are significantly influenced by the fuel composition, particularly the concentration of long-chain hydrocarbons and oxygenated compounds. Longer-chain hydrocarbons tend to promote high-temperature combustion, which can lead to increased NO_x emissions. On the other hand, B10 showed a shift toward shorter-chain alkanes and potentially lower NO_x emissions as biodiesel is known to reduce peak combustion temperatures and lowering the NO_x formation (Jahirul *et al.*, 2021). For HDPE10 and PP10, the presence of long-chain hydrocarbons can elevate in-cylinder temperatures, indirectly promoting NO_x formation, although combustion efficiency may be compromised due to poor volatility. However, PP10 showed a slightly more favourable composition with fewer heavy-end hydrocarbons than HDPE10, potentially contributing to better volatility and combustion. The exact impact of these changes on NO_x emissions would require further experimental validation, as other factors such as engine load, speed, and AF ratio also play significant roles in determining emission levels. The presence of

negative peak areas for some compounds, such as Tricosane ($C_{23}H_{48}$) and Tetradecane ($C_{14}H_{30}$), may indicate baseline correction issues or data noise (Bos *et al.*, 2020; Gras *et al.*, 2018; Sko *et al.*, 2022). While these negative values do not necessarily reflect the absence of these compounds, they suggest the need for refined data processing techniques to ensure accurate peak quantification. These anomalies should be addressed in future analyses to improve the reliability of the GC-FID results. The data follow expected patterns in terms of retention times and concentrations, indicating a robust chromatographic method and consistent sample analysis (Si *et al.*, 2023; Xu & Li, 2024).

The variation in hydrocarbon abundance across the different diesel blends indicates that each blend has a unique fuel profile. B10 showed a decrease in the concentration of long-chain hydrocarbons, while plastic-derived fuels of HDPE10 and PP10 displayed different profiles due to the presence of polymer-based hydrocarbons. The presence of these polymer-derived hydrocarbons in HDPE10 and PP10 likely contributes to a unique emission profile and could have implications for soot formation and particulate emissions. The GC-FID system used in this analysis is sensitive to the concentration of specific hydrocarbons, with shorter-chain hydrocarbons detected more easily than longer-chain compounds. The detection limitations of the system, especially for longer-chain alkanes, may lead to discrepancies in peak areas and compound identification (Drozdova *et al.*, 2013; Melder *et al.*, 2023; Salerno *et al.*, 2020). This highlights the importance of proper calibration and validation procedures to ensure that the detected data reflects the true fuel composition and provides accurate insights into the fuel properties. The GC-FID analysis of the diesel blends reveals the composition of n-alkanes and their influence on fuel properties, combustion behaviour, and NO_x emissions. The shift in composition with the inclusion of B10, HDPE10, and PP10 highlights the importance of understanding the impact of fuel composition on engine performance and emissions. The findings indicate that biodiesel can potentially lower NO_x emissions, while plastic-derived fuels may introduce different emission characteristics. The data also suggest that long-chain hydrocarbons may contribute to soot formation and elevated NO_x emissions, emphasizing the need for careful fuel formulation to balance emission reductions and combustion efficiency.

4.1.6 CHNS Elemental

Figure 4.10 illustrates the CHNS of the various tested samples. Table 4.7 shows the elemental composition of various fuels in percentage values. O element was obtained by subtracting the sum of C, H, N, and S from 100%. However, the S element was not detected. The S element was not detected due to several factors, including the low sulphur content in modern diesel fuels, the detection limits of the instrument, and the use of desulfurized fuels (de Aguiar *et al.*, 2024; Kolb *et al.*, 2024).

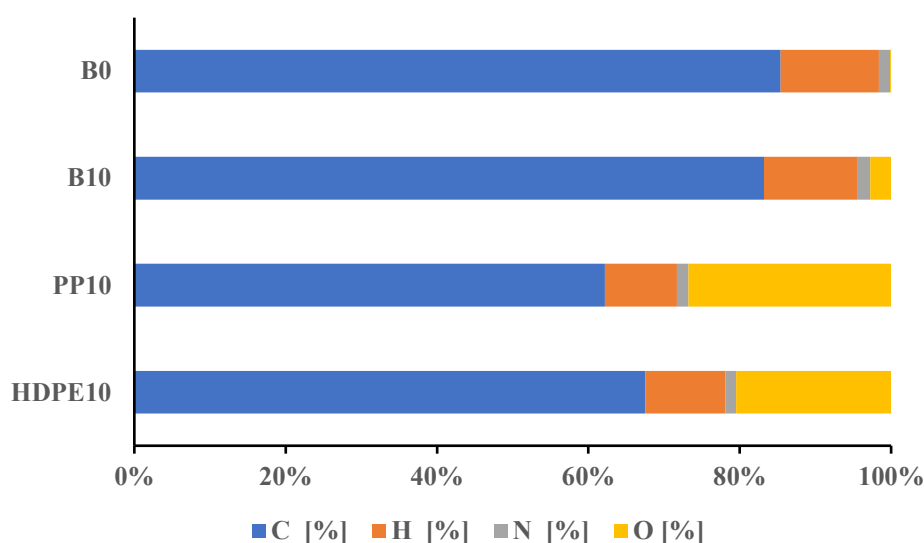


Figure 4.10 Comparison of CHNS elemental composition for different fuels

Table 4.7 Elemental composition of various fuels using the CHNS method

Element	B0	B10	HDPE10	PP10
C (%)	85.4	83.2	67.5	62.2
H (%)	13.01	12.4	10.6	9.5
N (%)	1.44	1.65	1.43	1.53
O (%)	0.15	2.75	20.47	26.77

The results showed B10 exhibited the highest carbon content (85.4%), followed by B10 (83.2%), representing a marginal reduction of 2.58% due to the incorporation of oxygenated biodiesel compounds. In contrast, HDPE10 (67.5%) and

PP10 (62.2%) showed more significant reductions in carbon content by 20.96% and 27.16% relative to B0, respectively. These reductions are attributable to the pyrolytic decomposition of plastic polymers, which generates lighter hydrocarbons and oxygenated compounds, thereby lowering the carbon concentration (Onwudili *et al.*, 2024).

Hydrogen content followed a similar trend. B0 had the highest hydrogen content (13.01%), with B10 (12.4%) showing a slight decline of 4.69%, maintaining its hydrocarbon-rich profile. HDPE10 (10.6%) and PP10 (9.5%) demonstrated considerable reductions of 18.52% and 26.98% compared to B0, respectively. This decline reflects the nature of plastic-derived fuels, which typically contain lower hydrogen saturation due to the fragmentation of polymer chains during pyrolysis (Medaiyese *et al.*, 2024). Nitrogen content remained relatively consistent across all samples. B10 (1.65%) showed a 14.58% increase compared to B0 (1.44%), likely due to nitrogenous residues present in biodiesel feedstocks. HDPE10 (1.43%) and PP10 (1.53%) exhibited negligible reductions of 0.69% and 6.25% from B0, respectively. These minimal variations indicate that plastic-derived fuels do not significantly alter the nitrogen load, suggesting a limited impact on fuel-bound NO_x emissions (Medaiyese *et al.*, 2024). The most pronounced difference was observed in oxygen content. PP10 contained the highest oxygen level (26.77%), which is over 178 times higher than B0 (0.15%), while HDPE10 (20.47%) showed a 135-fold increase. These elevated values are consistent with the FTIR findings (Figure 4.1), confirming the presence of oxygenated compounds in the plastic-derived fuels. B10 (2.75%) also showed increased oxygen content compared to B0, an 18.3-fold increase due to the ester functional groups naturally present in biodiesel (Zhang *et al.*, 2022; Zhong *et al.*, 2021).

These elemental differences have important implications. The higher carbon and hydrogen content in B0 and B10 supports superior energy density and efficient combustion. Conversely, the elevated oxygen content in HDPE10 and PP10 may facilitate more complete combustion but can also result in higher in-cylinder temperatures, potentially increasing thermal NO_x formation. However, since nitrogen content in HDPE10 and PP10 is comparable to that in B0, the contribution of fuel-

bound nitrogen to NO_x emissions is expected to be minimal (Medaiyese *et al.*, 2024; Zhang *et al.*, 2017). The CHNS analysis reveals significant differences in the elemental composition of the fuels, with B10 exhibiting superior energy density due to its higher carbon and hydrogen levels, while HDPE10 and PP10 show marked increases in oxygen content.

4.2 Performance of the Diesel Engine

This section examines the influence of various diesel blends on engine performance across different engine speeds and load conditions. A detailed analysis is carried out to understand the complex interplay of factors affecting performance, drawing on data obtained from a structured series of experiments. The experimental loads applied follow the ISO 8178 D2 test cycle, with constant engine speeds set at 2000 rpm and 2500 rpm.

4.2.1 Brake Power

The BP variation of the diesel engine running at different speeds and loads is presented in Figure 4.11. The actual usable power output of the engine from the conversion of chemical energy to mechanical energy is referred to as BP, and it is normally measured at the crankshaft of the engine. The BP increases with the increase of loads and speeds due to the increase of rpm and torque. Table 4.8 summarizes BP from various diesel fuels at specific loads and speeds. The BP results for B0, B10, HDPE10, and PP10 under various engine speeds and loads provide details on the performance of biodiesel and alternative fuels as shown in Figure 4.11 and Table 4.8. Among the tested fuels, B0 consistently delivers the highest BP due to its superior calorific value, which translates into greater energy release during combustion. The BP reductions for alternative fuels vary with speed. During 2000 rpm and 2500 rpm, B10 shows BP deviation range between -5.4% to +2.7% and -2.5% to +1.1%, HDPE10 between -7.0% to -0.3% and -3.3% to +1.6%, and PP10 between -5.7% to +1.0% and -1.3% to +1.3%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm),

alternative fuels produced slightly lower BP than B0 at most operating conditions. B10 shows a reduction by 3.2% to 0.2 kW and 0.9% to 0.53 kW, HDPE10 shows a reduction by 0.3% to 0.20 kW and 2.3% to 0.52 kW, and PP10 shows a slight increment by 1.0% to 0.21 kW and a reduction by 4.1% to 0.51 kW, respectively. This shows that the alternative fuels with lower volatility and calorific value limit combustion efficiency under light-duty conditions. At 2500 rpm and low loads (1 Nm and 2.5 Nm), alternative fuels show a slight improvement at most operating conditions. B10 gains an increment 1.1% to 0.26 kW and 0.3% to 0.65 kW, HDPE10 shows a reduction of 1.3% to 0.25 kW and an increase of 1.6% to 0.66 kW, and PP10 shows a reduction of 1.3% to 0.25 kW and an increase of 1.3% to 0.66 kW, respectively.

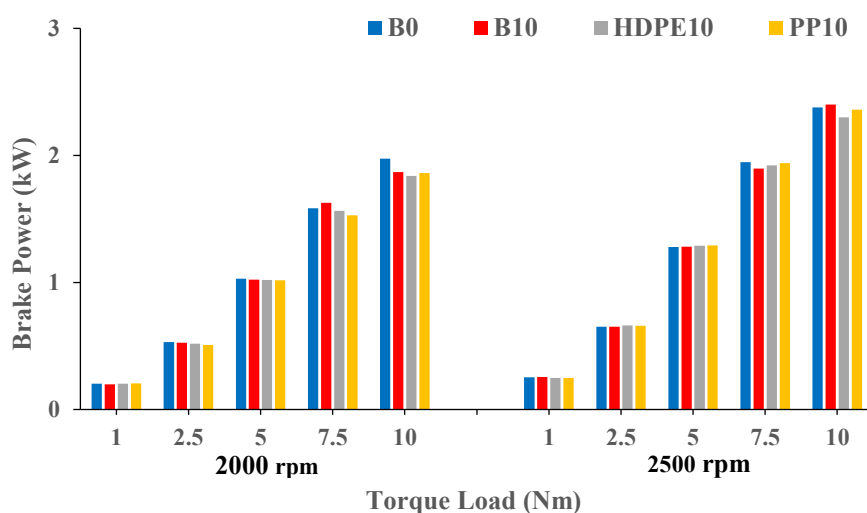


Figure 4.11 Variation of BP at different torque loads and engine speeds

Table 4.8 Summary of BP of biodiesel fuels in variation parameters

Speed (rpm)	Torque Load (Nm)	B0 (kW)	B10 (kW)	HDPE10 (kW)	PP10 (kW)
2000	1	0.20	0.2 (-3.2*)	0.20 (-0.3*)	0.21 (+1.0*)
	2.5	0.53	0.53 (-0.9*)	0.52 (-2.3*)	0.51 (-4.1*)
	5	1.03	1.02 (-0.8*)	1.02 (-0.9*)	1.02 (-1.3*)
	7.5	1.58	1.63 (+2.7*)	1.57 (-1.2*)	1.53 (-3.5*)
	10	1.98	1.87 (-5.4*)	1.84 (-7.0*)	1.86 (-5.7*)
2500	1	0.25	0.26 (+1.1*)	0.25 (-1.3*)	0.25 (-1.3*)
	2.5	0.65	0.65 (+0.3*)	0.66 (+1.6*)	0.66 (+1.3*)
	5	1.28	1.28 (+0.4*)	1.29 (+0.9*)	1.29 (+1.2*)
	7.5	1.95	1.90 (-2.5*)	1.92 (-1.3*)	1.94 (-0.4*)

10	2.36	2.40 (+0.9*)	2.30 (-3.3*)	2.36 (-0.8*)
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*The values in parentheses represent the deviation% increase (+) or decrease (-) in BP relative to B0

At 2000 rpm and medium load (5 Nm), B0 exhibits 1.03 kW BP while alternative fuels show a minor reduction to 0.8% to 1.02 kW for B10, 0.9% to 1.02 for HDPE10, and 1.3% to 1.02 kW for PP10. At 2500 rpm and medium load (5 Nm), B0 exhibits 1.28 kW while alternative fuels show increasing BP by 0.4% to 1.28 kW for B10, 0.9% to 1.29 kW for HDPE10, and 1.2% to 1.29 kW for PP10. These finding suggests that medium load provides a thermally favourable condition for the alternative fuels compared to B0. At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 shows BP readings of 1.58 kW and 1.98 kW, respectively. Only B10 shows increasing BP at 7.5 Nm with a value of 1.63 kW, an increase of 2.7%. The BP decreased to 1.87 kW, reduced by 5.4% followed by HDPE10 showed 1.57 kW and 1.84 kW, representing a reduction by 1.2% and 7.0% respectively, and PP10 showed 1.53 kW and 1.86 kW, representing a reduction by 3.5% and 5.7%, respectively.

At 2000 rpm and 10 Nm load, B0 achieves a BP of 1.98 kW, significantly outperforming B10, HDPE10, and PP10 by 5.4%, 7.0%, and 5.7%, respectively. These reductions align with findings from prior studies that demonstrated diesel blends with additives typically have lower calorific values than B0 (Mei *et al.*, 2020; Mikulski *et al.*, 2020). The physical properties of these fuels, such as viscosity and density, play a vital role in influencing BP. B10 exhibits higher viscosity from Figure 4.3 and density from Figure 4.4 than B0 can lead to less efficient atomization and delayed combustion, respectively. HDPE10 and PP10 show significant BP reductions compared to B0 in both speed and high loads. However, B10 demonstrates slightly improved BP under certain conditions due to its oxygenated nature, which enhances combustion stability. PP10, with its lower density and improved spray atomization characteristics, shows better BP performance under certain conditions, with a smaller reduction of 5.7% compared to 7.0% of HDPE10.

The chemical composition of the fuels analysed through FTIR from Figure 4.1 and GC-FID from Tables 4.3 to 4.6 further explains their performance differences. FTIR analysis of B10 highlights strong carbonyl (C=O) peaks, indicating the presence of FAME. These oxygenated compounds promote cleaner combustion but reduce the

energy density, contributing to slightly lower BP. For HDPE10 and PP10, GC-FID results from Tables 4.3 to 4.6 reveal higher concentrations of hydrocarbons derived from the pyrolysis process. These hydrocarbons exhibit reduced combustion efficiency due to variability in chain lengths and structures, which can hinder complete combustion (Tian *et al.*, 2022). Elemental composition analysis from CHNS in Table 4.10 reinforces these observations. B0 has a higher C-to-H ratio, which supports more complete combustion and higher BP. Conversely, B10 contains oxygen atoms from its FAME content, which lowers its overall energy density. At 2500 rpm and 5 Nm load, B0 achieves a BP of 1.28 kW, while B10 records a slightly reduced BP by 0.38% to 1.28 kW. Similarly, the lower calorific values of HDPE10 and PP10 from Figure 4.2 result in reduced BP under similar conditions. Shorter hydrocarbon chains in PP10 improve atomization, leading to a marginally better BP performance compared to HDPE10. At 2500 rpm and 10 Nm load, PP10 exhibits a minimal BP reduction of 0.8% compared to B0. Overall, the alternative fuels demonstrate acceptable BP performance with moderate reductions. These findings are consistent with previous studies by Huang *et al.* (2024) and Palani *et al.* (2022), underscoring the potential of biodiesel and pyrolysis fuels as viable diesel alternatives.

4.2.2 Brake-Specific Fuel Consumption

Figure 4.12 and Table 4.9 show the BSFC variation of the diesel engine operating at various speeds and loads. BSFC measures how much fuel a diesel engine requires for every unit of power produced. It fluctuates according to operating conditions, speed, and load, and represents engine efficiency. During 2000 rpm and 2500 rpm, B10 shows BSFC deviation range between -39.2% to 16.0% and -3.9% to 15.0%, HDPE10 between -40.9% to -21.5% and -4.7% to +9.2%, and PP10 between -54.2% to -15.5% and -8.6% to +3.3%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 shows BSFC of 1593 g/kWh and 734 g/kWh, respectively. B10 exhibits BSFC reduced by 39.2% to 969 g/kWh and 28.5% to 525 g/kWh, HDPE10 reduced by 40.9% to 941 g/kWh and 36.0% to 470 g/kWh, and PP10 reduced by 54.2% to 730 g/kWh and 39.4% to 445 g/kWh, respectively. The significant reduction in BSFC indicates that alternative fuels of biodiesel and plastic-derived fuels burn more efficiently under light-load conditions, possibly due to enhanced AF mixing and better

combustion stability. At 2500 rpm and low loads (1 Nm and 2.5 Nm), B0 exhibits BSFC of 901 g/kWh and 459 g/kWh, respectively. B10 shows BSFC increased by 15.0% to 1035 g/kWh and decreased by 3.9% to 441 g/kWh, HDPE10 shows an increment of 9.2% to 983 g/kWh and 3.5% to 475 g/kWh, and PP10 shows an increment of 3.3% to 930 g/kWh and a decrease of 1.6% to 452 g/kWh, respectively. The rise at 2500 rpm and load 1 Nm may be attributed to combustion instability and increased friction losses. In contrast, HDPE10 at 2.5 Nm condition showed a modest increase by 3.5% indicating more stable combustion behaviour.

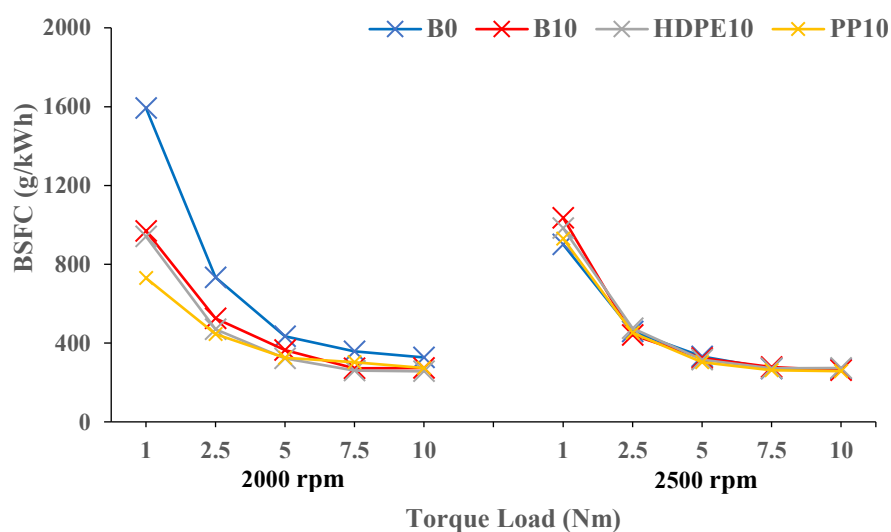


Figure 4.12 Variation of BSFC in different loads and speeds

Table 4.9 Summary BSFC of biodiesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (g/kWh)	B10 (g/kWh)	HDPE10 (g/kWh)	PP10 (g/kWh)
2000	1	1593	969 (-39.2*)	941 (-40.9*)	730 (-54.2*)
	2.5	734	525 (-28.5*)	470 (-36.0*)	445 (-39.4*)
	5	434	365 (-16.0*)	322 (-25.9*)	325 (-25.1*)
	7.5	357	272 (-23.9*)	260 (-27.1*)	302 (-15.5*)
	10	327	273 (-16.5*)	256 (-21.5*)	273 (-16.5*)
2500	1	901	1035 (+15.0*)	983 (+9.2*)	930 (+3.3*)
	2.5	459	441 (-3.9*)	475 (+3.5*)	452 (-1.6*)
	5	332	324 (-2.5*)	316 (-4.7*)	303 (-8.6*)
	7.5	269	279 (+3.6*)	272 (+1.1*)	263 (-2.6*)
	10	269	261 (-2.8*)	273 (+1.5*)	257 (-4.3*)

*The values in parentheses represent the deviation% increase (+) or decrease (-) in BSFC relative to B0

At 2000 rpm and medium load (5 Nm), B0 exhibits BSFC 434 g/kWh. Alternative fuels show a significant reduction in this operating condition. B10 shows BSFC reduced by 16.0% to 365 g/kWh, HDPE10 shows reduction by 25.9% to 322 g/kWh, and PP10 shows a reduction by 25.1% to 325 g/kWh. At 2500 rpm and medium load (5 Nm), B0 recorded BSFC to 332 g/kWh, while alternative fuels continued to outperform B0 with a slight reduction. B10 shows BSFC reduced by 2.5% to 324 g/kWh, HDPE10 shows a reduction by 4.7% to 316 g/kWh, and PP10 shows a reduction by 8.6% to 303 g/kWh. These findings highlight that alternative fuels reach optimal combustion efficiency under medium load conditions due to better cylinder pressure and combustion temperature.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 exhibits BSFC of 357 g/kWh and 327 g/kWh, respectively. Alternative fuels exhibit better BSFC compared to B0 at these operating conditions. B10 shows BSFC reduced by 23.9% to 272 g/kWh and 16.5% to 273 g/kWh, HDPE10 shows reduction by 27.1% to 260 g/kWh and 21.5% to 256 g/kWh, and PP10 shows reduction by 15.5% to 302 g/kWh and 16.5% to 273 g/kWh, respectively. These results show that HDPE10 provides strong combustion efficiency at high load operation, potentially due to its hydrocarbon structure despite its synthetic origin. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 exhibits BSFC 269 g/kWh for both loads. Alternative fuels show a slight fluctuation at this operational condition. B10 shows a slight increment by 3.6% to 279 g/kWh and a reduction by 2.8% to 261 g/kWh. HDPE10 shows a slight increment by 1.1% to 272 g/kWh and 1.5% to 273 g/kWh, and PP10 shows a reduction by 2.6% to 263 g/kWh and 4.3% to 257 g/kWh, respectively. PP10 continued to reduce BSFC at high load and speed, indicating better adaptability.

Incomplete combustion occurs in an engine running at low load (1 Nm and 2.5 Nm) because of several variables, including reduced cylinder pressure, longer combustion interval, and inefficient utilization of available air and fuel, thus influencing higher BSFC readings (Arjharn *et al.*, 2022; Rajendran *et al.*, 2023; Sivashankar *et al.*, 2018). The higher BSFC of these blends at this condition suggests poor fuel efficiency, which can be attributed to the need to improve combustion characteristics at low loads. FTIR analysis from Figure 4.1 reveals the presence of

oxygenated compounds from carbonyl groups that enhance combustion efficiency by facilitating more complete oxidation. The higher viscosity and density of biodiesel blends from Figures 4.3 and 4.4 could offset these benefits at higher loads by impairing atomization and mixing (Arunkumar *et al.*, 2023; Gülüm & Bilgin, 2018). At medium load (5 Nm), the BSFC of B10, HDPE10, and PP10 remains lower than B0, with a reduction range between 16.0% to 25.9%. The higher reduction from alternative fuels at this load is consistent with lower viscosities from Figure 4.3 and densities from Figure 4.4 compared to B0, as these properties favour improved atomization and combustion. GC-FID analysis from Tables 4.3 to 4.6 indicates a higher proportion of shorter-chain hydrocarbons in HDPE10 and PP10, which contributes to faster combustion and reduced fuel consumption (Han *et al.*, 2018). At higher loads, the BSFC of B10, HDPE10, and PP10 is reduced in the moderate range from 15.5% to 27.1% for 7.5 Nm and 10 Nm, respectively. HDPE10 and PP10 demonstrate superior performance due to their relatively lower densities from Figure 4.4, which enhance spray characteristics and combustion at higher loads, as supported by Lou *et al.* (2022).

At 2500 rpm, the trend in BSFC differs due to the influence of higher engine speed on fuel atomization and combustion. At a low torque of 1 Nm, B10, HDPE10, and PP10 exhibit increased BSFC compared to B0, with increases of 15.0%, 9.2%, and 3.3%, respectively. The trend increases by 3.5% for HDPE10, and vice versa for B10 and PP10, which shows a reduction of 3.9% and 1.6% for 2.5 Nm, respectively. These increases can be attributed to reduced combustion efficiency at higher speeds, where the higher viscosity from Figure 4.3 adversely affects fuel spray and atomization, as supported by Hoang *et al.* (2021) and Kim *et al.* (2020). At medium load (5 Nm), the alternative fuels demonstrated lower BSFC than B0 with a reduction range of 2.49% to 8.59%. This improvement aligns with findings from FTIR from Figure 4.1 and GC-FID analyses from Figures 4.5 to 4.9, which show that HDPE10 and PP10 contain shorter and more volatile hydrocarbon chains, leading to better combustion efficiency. At higher load, B10, HDPE10, and PP10 exhibit slightly fluctuating BSFC, with deviation percentage ranging from -2.8% to +3.6% for 7.5 Nm and 10 Nm. The slightly increased BSFC for HDPE10 may be attributed to the presence of longer hydrocarbon chains as observed in GC-FID results from Figures 4.6 to 4.9, which can cause slower combustion (Zhang *et al.*, 2022). In contrast, PP10 shows the most significant

reduction in BSFC, likely due to its superior atomization properties and shorter hydrocarbon chain structure.

The lower calorific values of biodiesel blends and pyrolysis fuels lead to higher BSFC, particularly under higher speeds and loads (Mengistu *et al.*, 2024; Yaqoob *et al.*, 2024b). Higher viscosity from Figure 4.3 and density from Figure 4.4 of B10 negatively impact atomization, particularly at higher speeds and loads. Conversely, the lower viscosity from Figure 4.3 and density from Figure 4.4 of HDPE10 and PP10 enhance spray characteristics, contributing to improved BSFC at moderate and high loads. FTIR and GC-FID analyses from Figure 4.1 and Figures 4.6 to 4.9 show that B10 contains oxygenated compounds, while HDPE10 and PP10 comprise hydrocarbons derived from pyrolysis. The oxygen content in B10 supports more complete combustion but lowers its energy density, leading to marginally higher BSFC under certain conditions. HDPE10 and PP10 improve combustion efficiency and reduce BSFC as observed at high loads. The BSFC trends for B10, HDPE10, and PP10 demonstrate their potential as alternative fuels with acceptable performance compared to B0 (Sanjeevannavar *et al.*, 2022; Vohra *et al.*, 2020). The biodiesel blend and pyrolysis-derived fuels exhibit competitive BSFC, particularly under medium and high conditions. These findings align with previous studies, emphasizing the role of optimizing fuel properties in enhancing the fuel efficiency of alternative fuels (Huang *et al.*, 2024; Palani *et al.*, 2022).

4.2.3 Brake Thermal Efficiency

Figure 4.13 and Table 4.10 depict that the diesel engine's variation in BTE varies depending on the loads and speeds. The BTE calculates the efficiency of heat-to-work conversion. During 2000 rpm and 2500 rpm, B10 shows BTE deviation range between +20.8% to 66.9% and -11.8% to 5.5%, HDPE10 between 19.8% to 73.5% and -6.3% to +7.4%, and PP10 between 18.5% to 118.7% and -3.0% to +9.6%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 exhibits BTE 5.0% and 10.7%, respectively. Alternative fuels showed a substantial improvement in BTE over B0 under low-load conditions. B10 shows BTE increment by 66.9% to 8.3% and

41.8% to 15.2%, HDPE10 shows BTE value increased by 73.5% to 8.6% and 60.0% to 17.2%, and PP10 shows BTE value increased by 118.7% to 10.8% and 65.3% to 17.8%, respectively. These improvements suggest better AF mixing and lower ignition delays from alternative fuels that support more complete combustion under low-load conditions. At 2500 rpm and low loads (1 Nm and 2.5 Nm), the performance trends for BTE reversed. B0 displays BTE by 8.8% and 17.2%, respectively. B10 shows a BTE value decreased by 11.8% to 7.7% and increased by 5.5% to 18.1%, HDPE10 shows a reduction by 6.3% to 8.2% and 1.4% to 16.9%, and PP10 shows a reduction by 3.0% to 8.5% and slightly increased by 1.8% to 17.5%, respectively. This suggests that combustion at high speed and low loads may be suboptimal for alternative fuels due to increased frictional losses and reduced cylinder pressure.

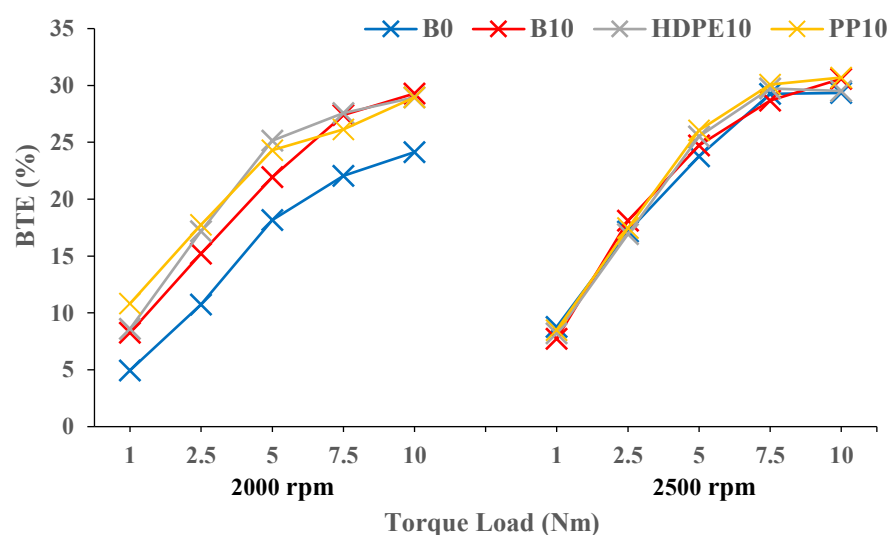


Figure 4.13 Variation of BTE in different loads and speeds

Table 4.10 Summary of BTE of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (%)	B10 (%)	HDPE10 (%)	PP10 (%)
2000	1	5.0	8.3 (+66.9*)	8.6 (+73.5)	10.8 (+118.7*)
	2.5	10.7	15.2 (+41.8*)	17.2 (+60.0)	17.8 (+65.3*)
	5	18.2	21.9 (+20.8*)	25.1 (+38.4)	24.3 (+33.7*)
	7.5	22.1	27.4 (+24.2*)	27.6 (+25.0)	26.2 (+18.5*)
	10	24.2	29.3 (+21.3*)	28.9 (+19.8)	29.0 (+19.9*)
2500	1	8.8	7.7 (-11.8*)	8.2 (-6.3*)	8.5 (-3.0*)

2.5	17.2	18.1 (+5.5*)	16.9 (-1.4*)	17.5 (+1.8*)
5	23.8	24.7 (+4.0*)	25.5 (+7.4*)	26.0 (+9.6*)
7.5	29.3	28.7 (-2.1*)	29.7 (+1.6*)	30.1 (+2.8*)
10	29.3	30.6 (+4.3*)	29.5 (+0.6*)	30.7 (+4.6*)

*The values in parentheses represent the deviation% increase (+) or decrease (-) in BTE relative to B0

At 2000 rpm and medium load (5 Nm), B0 displays BTE for 18.2%. Alternative fuels show BTE by 21.9%, 25.1%, and 24.3%, representing an increase by 20.8%, 38.4%, and 33.7% for B10, HDPE10, and PP10, respectively. These increases reflect enhanced combustion efficiency under balanced mechanical conditions. At 2500 rpm and medium load (5 Nm), B0 shows BTE by 23.8%. B10 shows BTE increased by 4.0% to 24.7%, HDPE10 and PP10 show an increment of BTE value by 7.4% to 25.5% and 9.6% to 26.04%. These findings assure that medium load operation conditions offer stable and efficient thermal conversion. Under higher load conditions (7.5 Nm and 10 Nm), BTE trends remain almost positive for all parameters for the overall results. At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 displays BTE for 22.1% and 24.2%. B10 shows 27.4% and 29.3%, accounting for an increasing trend of 24.2% and 21.3%, respectively. HDPE10 shows 27.6% and 28.9%, showing an increasing trend by 25.0% and 19.8%, while PP10 shows 26.2% and 29.0%, also showing an increasing trend by 18.5% and 19.9%, respectively. The trends indicate sustained combustion efficiency under thermal stress. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 exhibits BTE for 29.3% for both operating conditions. B10 shows BTE for 28.7% and 30.6%, a decrease of 2.1% and an increase of 4.3%. HDPE10 shows BTE for 29.7% and 29.5%, slightly increased by 1.6% and 0.6%, while PP10 shows BTE for 30.1% and 30.7%, increased by 2.8% and 4.6%, respectively. This suggests that plastic-derived fuels adapt more effectively to high-speed and load conditions due to volatility and energy content, particularly PP10.

At 2000 rpm and low loads (1 Nm and 2.5 Nm), alternative fuels show a significant increase in BTE from 41.8% to 118.7%. These increases are attributed to the higher oxygen content in B10 and the better combustion characteristics of pyrolysis fuels like HDPE10 and PP10. FTIR analysis from Table 4.1 shows that the oxygenated functional groups in B10 promote more complete combustion, enhancing thermal efficiency, as supported by Kumar *et al.* (2018) and Tamilvanan *et al.* (2021). Additionally, the shorter hydrocarbon chains in HDPE10 and PP10, as indicated by

GC-FID from Figures 4.6 to 4.9, improve atomization and fuel-air mixing, resulting in enhanced combustion efficiency, as supported by He *et al.* (2021) and Redel-Macías *et al.* (2021). As load increases, the trend continues with BTE improving significantly for all biodiesel blends. The relatively lower calorific value of alternative fuels from Figure 4.2 is offset by the improved combustion efficiency at higher loads, as supported by Ağbulut *et al.* (2020). PP10 consistently demonstrates better BTE than HDPE10, which aligns with its lower viscosity and density from Figures 4.3 and 4.4, respectively.

At an engine speed of 2500 rpm, the BTE of biodiesel blends exhibits a more complex trend. At low loads (1 Nm and 2.5 Nm), increments varied from 1.8% to 5.5% while reductions showed as high as 11.8% compared to B0. The significant reduction in B10 and HDPE10 due to higher viscosity from Figure 4.3, which adversely affects atomization and combustion at higher speeds and lower loads (Kumar *et al.*, 2018). However, PP10 performs relatively better due to its lower viscosity and better atomization characteristics. At medium load (5 Nm), all alternative fuels outperform B0 in BTE. The increase is most pronounced for PP10 by 9.6%, followed by HDPE10 by 7.4% and B10 by 4.0%. This aligns with the calorific value from Figure 4.2 and combustion properties of these fuels, where the hydrocarbons in HDPE10 and PP10 provide a balanced trade-off between energy content and combustion efficiency. FTIR from Figure 4.1 and GC-FID analyses from Figures 4.6 to 4.9 further confirm that shorter hydrocarbon chains in PP10 contribute to faster combustion, enhancing thermal efficiency under moderate loads. At high loads (7.5 Nm and 10 Nm), alternative fuels continue to show improvements in BTE with a slight increment, the highest by 4.6%.

B0 exhibits the highest calorific value from Figure 4.2, contributing to its superior energy density and BTE under certain conditions. However, the lower calorific values of B10, HDPE10, and PP10 are offset by their improved combustion efficiency, resulting in competitive BTE values, particularly under higher loads (Wasiu, 2019). Higher viscosity from Figure 4.3 and density from Figure 4.4 in B10 reduces its atomization quality, especially at higher speeds. In contrast, the lower viscosity from Figure 4.3 and density from Figure 4.4 of HDPE10 and PP10 promote

better atomization and combustion, contributing to improved BTE under varying conditions. The slightly higher BTE of PP10 compared to HDPE10 can be linked to its superior spray characteristics, which optimize AF mixing and combustion. FTIR analysis from Figure 4.1 highlights the presence of oxygenated functional groups in B10 that enhance combustion efficiency by promoting complete oxidation. Meanwhile, GC-FID data from Figures 4.6 to 4.9 show that HDPE10 and PP10 contain a higher proportion of shorter hydrocarbon chains, which burn more efficiently and contribute to higher BTE, as supported by Rao *et al.* (2020). CHNS analysis from Figure 4.10 reveals that B0 has the highest C/H ratio, resulting in more energy release during combustion. However, the oxygen content in B10 supports more complete combustion, enhancing thermal efficiency, especially under low and moderate loads. The BTE analysis of biodiesel blends demonstrates their potential as efficient alternatives to B0. While B0 maintains a consistent baseline due to its higher calorific value, PP10 and HDPE10 exhibit good BTE due to their improved combustion properties.

The low viscosity of plastic-derived diesel fuels from Figure 4.3 provides fluent flow and higher energy output as reflected by the BTE value, as supported by Ramesh *et al.* (2022) and Sanjeevannavar *et al.* (2022). This trend continues across increasing load levels, suggesting that biodiesel and plastic additives significantly improve efficiency. The trend of increasing BTE with higher loads across all blends and speeds is typical behaviour as the engine works more efficiently under higher loads (Man *et al.*, 2016; Maroa *et al.*, 2021; Ramesh *et al.*, 2022). HDPE10 and PP10 consistently demonstrate better BTE at higher loads, suggesting the plastic additives contribute to greater fuel efficiency of engine performance.

4.3 Emissions of the Diesel Engine

This section examines the CO, CO₂, HC, and NO_x emissions from the Yanmar L48N6-MTMYRI diesel engine. O₂ is also measured to understand how the oxygen content in fuel eases the combustion process.

4.3.1 CO Emissions

Figure 4.14 and Table 4.11 display the CO emissions from the four different fuel types under various operating conditions. CO emissions are generally a result of incomplete combustion due to insufficient oxygen, non-ideal atomization, or lower cetane numbers. The trend shows increasing CO emissions as loads increase, especially at lower speeds. The increase in CO emissions for the alternative fuels varies with speed. During 2000 rpm and 2500 rpm, B10 shows CO emissions deviations range between +14.0% to 57.1% and +3.3% to +42.9%, HDPE10 between 12.5% to 30.3% and -40.7%, PP10 shows -14.3% to -8.3% and +16.7% to 83.3%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 records CO emissions by 2.9×10^{-4} g/kWh and 2.2×10^{-4} g/kWh, respectively. B10 shows CO emissions increased by 37.5% to 4.0×10^{-4} g/kWh and 50.0% to 3.2×10^{-4} g/kWh, respectively. HDPE10 shows CO emissions value increased by 12.5% to 3.2×10^{-4} g/kWh and 16.7% to 2.5×10^{-4} g/kWh, while PP10 shows decrement by 12.5% to 2.51×10^{-4} g/kWh and constant to 2.15×10^{-4} g/kWh, respectively. Reduction of CO emissions in PP10 highlighted the ability to sustain cleaner combustion at low load and temperature conditions. At 2500 rpm and low loads (1 Nm and 2.5 Nm), B0 displays CO emissions by 2.5×10^{-4} g/kWh and 2.2×10^{-4} g/kWh, respectively. B10 shows CO emissions increased by 42.9% to 3.6×10^{-4} g/kWh and 33.3% to 2.9×10^{-4} g/kWh, HDPE10 shows constant deviation, while PP10 shows an increment by 71.4% to 4.3×10^{-4} g/kWh and 83.3% to 4.0×10^{-4} g/kWh, respectively. HDPE10 shows a constant result of CO emissions compared to B0, indicating stable CO behaviour due to more consistent volatility and better thermal conditions.

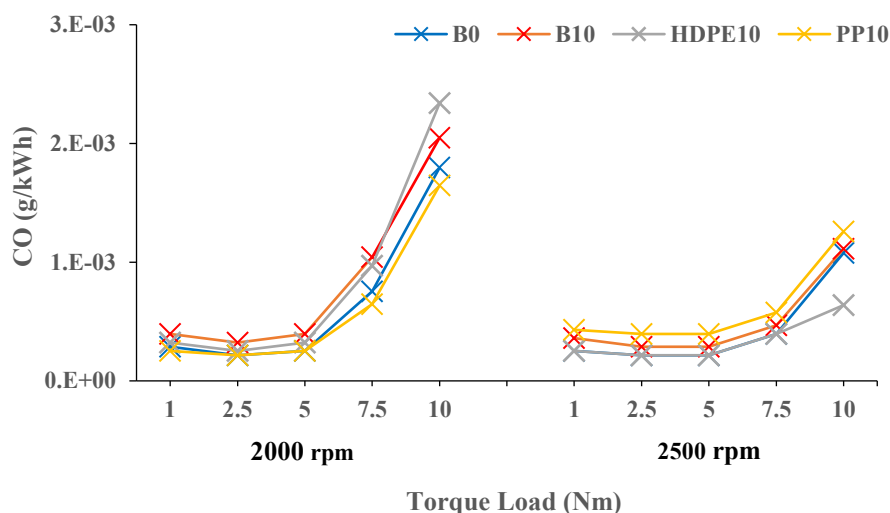


Figure 4.14 Variation of CO emissions in different loads and speeds

Table 4.11 Summary of CO emissions of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 in 10^{-4} (g/kWh)	B10 in 10^{-4} (g/kWh)	HDPE10 in 10^{-4} (g/kWh)	PP10 in 10^{-4} (g/kWh)
2000	1	2.9	4.0 (+37.5*)	3.2 (+12.5*)	2.5 (-12.5*)
	2.5	2.2	3.2 (+50.0*)	2.5 (+16.7*)	2.2 (constant*)
	5	2.5	4.0 (+57.1*)	3.2 (+28.6*)	2.5 (constant*)
	7.5	7.5	10.4 (+38.1*)	9.7 (+28.6*)	6.5 (-14.3*)
	10	18.0	20.5 (+14.0*)	23.4 (+30.3*)	16.5 (-8.3*)
2500	1	2.5	3.6 (+42.9*)	2.5 (constant*)	4.3 (+71.4*)
	2.5	2.2	2.9 (+33.3*)	2.2 (constant*)	4.0 (+83.3*)
	5	2.2	2.9 (+33.3*)	2.2 (constant*)	4.0 (+83.3*)
	7.5	4.0	4.7 (+18.2*)	4.0 (constant*)	5.8 (+45.5*)
	10	10.8	11.1 (+3.3*)	6.4 (-40.7*)	12.6 (+16.7*)

*The values in parentheses represent the deviation% increase (+) or decrease (-) in CO relative to B0

At 2000 rpm and medium load (5 Nm), B0 exhibits CO emissions by 2.5×10^{-4} g/kWh. B10 shows CO emissions increased by 57.1% to 4.0×10^{-4} g/kWh, HDPE10 shows increment by 28.6% to 3.2×10^{-4} g/kWh, and PP10 shows constant value by 2.5×10^{-4} g/kWh compared to B0. PP10 shows a more balanced combustion profile at the medium load condition. At 2500 rpm and medium load (5 Nm), B0 displays CO emissions by 2.2×10^{-4} g/kWh. B10 and PP10 show an increment of CO emissions by 33.3% to 2.9×10^{-4} g/kWh and 83.3% to 4.0×10^{-4} g/kWh, respectively. While

HDPE10 displays a constant value at B0. These results suggest HDPE10 maintains more stable CO emissions at a medium load of 5 Nm.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 records CO emissions by 7.5×10^{-4} g/kWh and 18.0×10^{-4} g/kWh, respectively. B10 and HDPE10 show an increase in CO emissions. B10 shows increment by 38.1% to 10.4×10^{-4} g/kWh and 14.0% to 20.5×10^{-4} g/kWh, and HDPE10 shows increment by 28.6% to 9.7×10^{-4} g/kWh and 30.3% to 20.5×10^{-4} g/kWh, respectively. In contrast, PP10 shows a decrease of CO emissions by 14.3% to 6.5×10^{-4} g/kWh and 8.3% to 16.5×10^{-4} g/kWh, respectively. PP10 indicates a more balanced combustion profile at the medium load condition. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 exhibits CO emissions of 4.0×10^{-4} g/kWh and 10.8×10^{-4} g/kWh, respectively. B10 and PP10 show an increase in CO emissions. B10 shows increment by 18.2% to 4.7×10^{-4} g/kWh and 3.3% to 11.1×10^{-4} g/kWh, while PP10 shows increment by 45.5% to 5.8×10^{-4} g/kWh and 16.7% to 12.6×10^{-4} g/kWh, respectively. HDPE10 shows a constant value of 4.0×10^{-4} g/kWh and decreased by 40.7% to 6.4×10^{-4} g/kWh. This result recommends that HDPE10 maintains more stable CO emissions under high-load conditions.

During the 2000 rpm parameter, B10 and HDPE10 show a significant increment of CO emissions, varying from 12.5% to 57.14%. While PP10 shows a constant value, and decrement varied from 8.31% to 14.29%. Reduction in PP10 indicates improved combustion efficiency due to its lower kinematic viscosity from Figure 4.3 and superior atomization characteristics, as revealed in previous GCFID from Figure 4.6 to 4.9 and density analyses from Figure 4.4. During the 2500 rpm parameter, B10 increased CO emissions varied from 3.3% to 42.9%. The trend is also the same as PP10, which shows increasing CO emissions varying from 16.7% to 83.3%. This aligns with CHNS analysis findings from Figure 4.10 that suggest the shorter hydrocarbon chains and lower viscosity of PP10 from Figure 4.2 promote better mixing and oxidation during combustion. While HDPE10 shows mostly similar values of CO emissions and a reduction value of 40.7% compared to B0. This can be attributed to its relatively higher calorific value from Figure 4.2 and the favourable oxygen-to-carbon ratio for more complete combustion as highlighted in CHNS elemental analyses from Figure 4.10. Alternative fuels with lower calorific values from

Figure 4.2 tend to show higher CO emissions at specific loads and speeds, primarily due to incomplete energy release during combustion. This is supported by previous studies on FAME fuels where incomplete oxidation of carbon occurs at lower combustion temperatures (Babamohammadi *et al.*, 2025; Ghaffarzadeh *et al.*, 2020).

This is supported by FTIR spectra from Figure 4.1, showing prominent carbonyl functional groups in biodiesel. HDPE10 benefits from relatively shorter hydrocarbon chains, resulting in lower CO emissions at higher speeds (Modi & Patel, 2023). In contrast, PP10 exhibits excellent atomization and volatility characteristics due to its lower viscosity and shorter hydrocarbon chains, reducing CO emissions at low speed (Janyalertadun *et al.*, 2017; Mustayen *et al.*, 2023). Despite the increase in CO emissions, all tested fuels remained within the allowable CO limits as specified by ISO 8178 and EPA Tier 4 standards.

4.3.2 CO₂ Emissions

Figure 4.15 and Table 4.12 show CO₂ emissions for the different diesel fuels running on the diesel engine under various operating conditions. CO₂, a GHG emission, contributes to global warming by trapping heat and causing climate change. During 2000 rpm and 2500 rpm, B10 shows CO₂ emissions deviation range from +19.3% to +50.0% and +37.0% to +93.8%, HDPE10 between -20.0% to +15.0% and -1.8% to +6.3%, PP10 between -28.1% to +2.5% and +39.1% to 52.2%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 recorded CO₂ emissions of 126.9 g/kWh and 152.3 g/kWh, respectively. CO₂ emissions of B10 recorded a constant value of 126.9 g/kWh and an increase of 20.8% to 184.1 g/kWh, HDPE10 recorded a 20.0% reduction to 101.6 g/kWh and a slight increase of 4.2% to 158.7 g/kWh, and PP10 recorded a 20.0% reduction to 101.6% and 4.2% to 146.0 g/kWh, respectively. CO₂ emissions reduction at 1 Nm suggests cleaner combustion behaviour for plastic-derived fuels. As the load increases to 2.5 Nm, PP10 maintains its efficient combustion by slightly reducing CO₂ emissions to 4.2%. At 2500 rpm and low loads (1 Nm and 2.5 Nm), the emissions trend changed significantly. B0 shows CO₂ emissions by 101.6 g/kWh and 146.0 g/kWh, respectively. Alternative fuels recorded significant increases

in CO₂ emissions. B10 shows an increment by 93.8% to 196.8 g/kWh and 52.2% to 222.2 g/kWh, respectively. HDPE10 shows an increment by 6.3% to 107.9 g/kWh and a constant value of 146.0 g/kWh, while PP10 shows an increment of 43.8% to 146.0 g/kWh and 52.2% to 222.1 g/kWh. The CO₂ emissions rose sharply from B10 might be due to increased fuel consumption or higher oxidation efficiency.

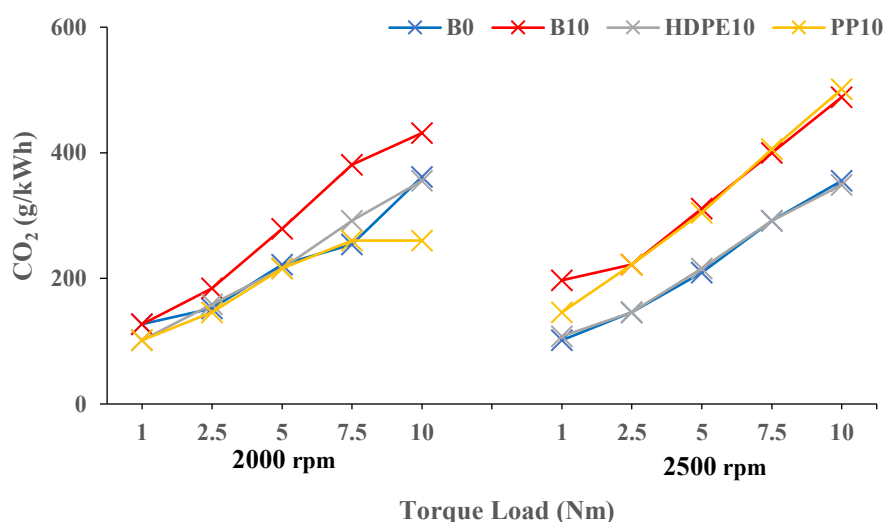


Figure 4.15 Variation of CO₂ exhaust emissions in different loads and speeds

Table 4.12 Summary of CO₂ emissions of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (g/kWh)	B10, (g/kWh)	HDPE10 (g/kWh)	PP10 (g/kWh)
2000	1	126.9	126.9 (constant*)	101.6 (-20.0*)	101.6 (-20.0*)
	2.5	152.3	184.1 (+20.8*)	158.7 (+4.2*)	146.0 (-4.2*)
	5	222.2	279.3 (+25.7*)	215.8 (-2.9*)	215.8 (-2.9*)
	7.5	253.9	380.8 (+50.0*)	292.0 (+15.0*)	260.2 (+2.5*)
	10	361.8	431.6 (+19.3*)	355.4 (-1.8*)	260.2 (-28.1*)
2500	1	101.6	196.8 (+93.8*)	107.9 (+6.3*)	146.0 (+43.8*)
	2.5	146.0	222.2 (+52.2*)	146.0 (constant*)	222.1 (+52.2*)
	5	209.5	311.0 (+48.5*)	216.0 (+3.0*)	304.7 (+45.5*)
	7.5	292.0	400.0 (+37.0*)	292.0 (constant*)	406.2 (+39.1*)
	10	355.4	488.7 (+37.5*)	349.1 (-1.8*)	501.4 (+41.1*)

*The values in parentheses represent the deviation% increase (+) or decrease (-) in CO₂ relative to B0

At 2000 rpm and medium load (5 Nm), B0 shows CO₂ emissions of 222.2 g/kWh. B10 shows an increment in CO₂ emissions by 25.7% to 279.3 g/kWh, while both plastic-derived fuels show a constant decrement by 2.9% to 215.8 g/kWh. B10 generated the highest CO₂ emissions, indicating enhanced combustion, and producing more carbon output aligns with its oxygen content, facilitating enhanced combustion. Plastic-derived fuels suggest more favourable combustion efficiency with a slight reduction of CO₂ emissions. At 2500 rpm and medium load (5 Nm), B0 shows CO₂ emissions of 209.5 g/kWh. B10 and PP10 show a significant increment by 48.5% to 311.0 g/kWh and 45.5% to 304.7 g/kWh, respectively. HDPE10 shows a slight increment by 3.0% to 216.0 g/kWh. Significant CO₂ emissions from B10 and PP10 reflect higher carbon oxidation, and minimal emissions from HDPE10 indicate more balanced combustion.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 shows CO₂ emissions of 253.9 g/kWh and 361.8 g/kWh, respectively. B10 aggressively produces CO₂ emissions by 50.0% more to 380.8 g/kWh and 19.3% to 431.6 g/kWh, respectively. HDPE10 moderately emits CO₂ emissions by 15.0% to 292.0 g/kWh and slightly reduces by 1.8% to 355.4 g/kWh, while PP10 shows a slight increase by 2.5% to 260.2 g/kWh and reduces significantly by 28.1% to 260.2 g/kWh, respectively. The significant reduction of CO₂ emissions from PP10 by 28.1% and a slight reduction from HDPE10 by 1.8% highlight energy content limitations that reduced full carbon oxidation. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 emits CO₂ emissions by 292.0 g/kWh and 355.4 g/kWh, respectively. B10 shows CO₂ emissions increased by 37.0% to 400.0 g/kWh and 37.5% to 488.7 g/kWh, HDPE10 shows constant CO₂ emissions at 291.962 g/kWh and slightly reduced by 1.8% to 349.1 g/kWh, while PP10 shows an increment by 39.1% to 406.2 g/kWh and 41.1% to 501.4 g/kWh, respectively. The trend by HDPE10 suggests that the fuel offers better carbon efficiency under high loads and high-speed conditions.

The highest calorific value from B0, assisted by Figure 4.2, shows consistent CO₂ emissions, indicating superior energy content and efficient combustion. In contrast, B10, with a slightly lower calorific value, produces higher CO₂ emissions at medium and high loads due to its oxygenated structure, promoting complete

combustion. HDPE10 and PP10 have varying CO₂ emissions because of the different densities and viscosities, as supported by Figures 4.4 and 4.3, respectively. Higher viscosity from HDPE10 results in delayed atomization and incomplete combustion, particularly at low and high loads (Gülüm & Bilgin, 2018; Niță *et al.*, 2022). Despite the fuel types, lower viscosity from PP10 improves atomization and contributes to higher emissions at medium and high loads (Chandrasekaran *et al.*, 2020; Tobar *et al.*, 2024). FTIR and GCFID analyses from Figures 4.1 and 4.6 to 4.9 confirm the presence of long-chain hydrocarbons in HDPE10 and PP10. Shorter hydrocarbon chains in PP10 enable better atomization and oxidation compared to HDPE10, leading to improved combustion at higher loads (He *et al.*, 2021). B10 consistently demonstrates higher CO₂ emissions, particularly at medium and high loads. HDPE10 and PP10 show variable trends, with PP10 performing better in terms of combustion efficiency due to its hydrocarbon structure.

In comparison to B0, both plastic-derived diesel fuels produce more CO₂ emissions, especially at higher loads at 2500 rpm. This implies that adding PP and HDPE additives improves combustion, as supported by Saha *et al.* (2024) and Kumar *et al.* (2018). The effect of speed on CO₂ emissions is noticeable, particularly for B10 and HDPE10. At higher speeds, CO₂ emissions remain consistent to indicating more across the loads applied, indicating more stable and efficient combustion of the engine. Previous studies confirmed that diesel blends with HDPE and PP additives can cut CO₂ emissions in diesel engines, especially when the engine is running at a lower speed and carrying a heavier load (Senthilkumar & Sankaranarayanan, 2016; Singh *et al.*, 2020). Lower viscosity makes the fuel blends atomized and mixed with air at the maximum rate, resulting in more complete combustion (Ogunkunle & Ahmed, 2021; Singh *et al.*, 2018; Venkatesan *et al.*, 2023). Although current emission regulations, such as EU Stage V and U.S. EPA Tier 4 Final, do not directly limit CO₂ emissions, the increased CO₂ emissions observed in HDPE10 and PP10 blends indicate a complete combustion process.

4.3.3 HC Emissions

The HC emissions are displayed in Figure 4.16. Table 4.13 assembles the HC emissions from diesel fuels at specific loads and speeds. The trend shows increasing HC emissions as load increases, with B10 showing a significant reduction at higher speeds. During 2000 rpm and 2500 rpm, B10 shows HC emissions deviation range between -25.0% to -19.2% and -69.6% to -38.5%, HDPE10 between +12.5% to 23.1% and 12.5% to 30.8%, and PP10 between +12.5% to 23.1% and -25.0% to +4.0%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 recorded HC emissions by 0.034 g/kWh and 0.048 g/kWh, respectively. B10 shows HC emissions at a constant value of 0.034 g/kWh and a reduction by 20.8% to 0.038 g/kWh. HDPE10 shows a significant increment by 17.7% to 0.04 g/kWh and 12.5% to 0.054 g/kWh, while PP10 also shows a significant increment by 17.7% to 0.04 g/kWh and 16.7% to 0.056 g/kWh, respectively. The significant reduction of HC emissions from B10 indicates cleaner combustion with oxygenated biodiesel fuel, which differs from plastic-derived fuels. Higher kinematic viscosity from Figure 4.3 and density from Figure 4.4 of plastic-derived fuels, which hinder atomization and mixing, leading to incomplete combustion. FTIR analysis from Figure 4.1 confirms the presence of long-chain hydrocarbons in HDPE10 and PP10, contributing to this behaviour. At 2500 rpm and low loads (1 Nm and 2.5 Nm), B0 recorded HC emissions of 0.032 g/kWh and 0.046 g/kWh, respectively. B10 improved HC emissions with a significant reduction by 50.0% to 0.016 g/kWh and 69.6% to 0.014 g/kWh. PP10 also shows a similar trend of significant reduction by 25.0% to 0.024 g/kWh and reduced by 8.7% to 0.042 g/kWh, respectively, while HDPE10 shows vice versa. HDPE10 displays an increment by 12.5% to 0.036 g/kWh and 13.0% to 0.052 g/kWh, respectively. The significant reduction of HC from B10 indicates that higher engine speed and low loads enhance biodiesel oxidation.

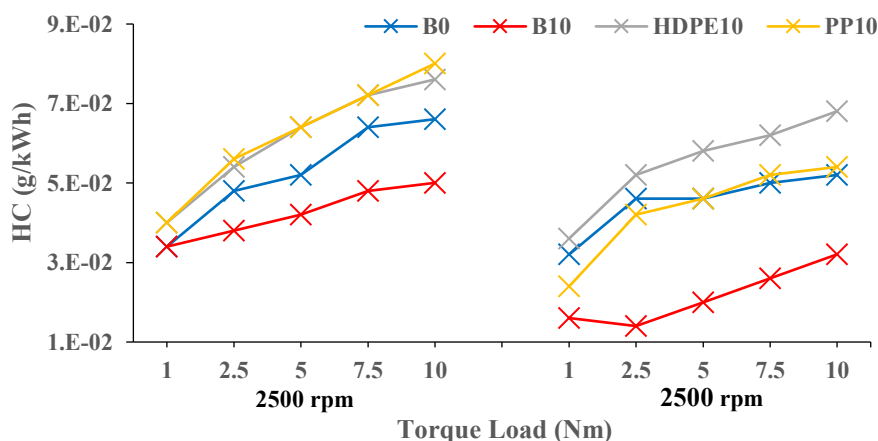


Figure 4.16 Variation of HC emissions in different loads and speeds

Table 4.13 Summary of HC emissions of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (g/kWh)	B10 (g/kWh)	HDPE10 (g/kWh)	PP10 (g/kWh)
2000	1	0.20	0.034 (constant*)	0.040 (+17.7*)	0.040 (+17.7*)
	2.5	0.53	0.038 (-20.8*)	0.054 (+12.5*)	0.056 (+16.7*)
	5	1.03	0.042 (-19.2*)	0.064 (+23.1*)	0.064 (+23.1*)
	7.5	1.58	0.048 (-25.0*)	0.072 (+12.5*)	0.072 (+12.5*)
	10	1.98	0.050 (-24.2*)	0.076 (+15.2*)	0.08 (+21.2*)
2500	1	0.25	0.016 (-50.0*)	0.036 (+12.5*)	0.024 (-25.0*)
	2.5	0.65	0.014 (-69.6*)	0.052 (+13.0*)	0.042 (-8.7*)
	5	1.28	0.020 (-56.5*)	0.058 (+26.1*)	0.046 (constant*)
	7.5	1.95	0.026 (-48.0*)	0.062 (+24.0*)	0.052 (+4.0*)
	10	2.36	0.032 (-38.5*)	0.068 (+30.8*)	0.054 (+3.9*)

*The values in parentheses represent the deviation% increase (+) or decrease (-) in HC relative to B0

At 2000 rpm and medium load (5 Nm), B0 recorded HC emissions of 0.052 g/kWh. B10 showed a 19.2% reduction to 0.042 g/kWh. Both plastic-derived fuels increased HC emissions by 23.1% to 0.064 g/kWh. HC reduction from B10 shows improved combustion as the load and in-cylinder temperature increase. B10 persistently displayed good combustion efficiency; HDPE10 and PP10 showed moderate and stable combustion. HDPE10 and PP10 exhibit increases by 23.1% indicating incomplete combustion due to poor atomization as influenced by their higher density and longer hydrocarbon chains observed in GCFID analysis, as supported by Figures 4.6 to 4.9. At 2500 rpm and medium load (5 Nm), HC emissions

exhibit 0.046 g/kWh for B0. B10 significantly reduced HC emissions by 56.5% to 0.02 g/kWh. PP10 displays increased HC emissions by 26.1% to 0.058 g/kWh and HDPE10 shows a constant value compared with B0. B10 is reinforcing its suitability under high speed and medium load. B10 reduces the highest HC emissions by 56.5% reinforcing its role in improving combustion efficiency. HDPE10 shows a significant increase of 26.1% attributed to the incomplete combustion of long-chain hydrocarbons, as confirmed by FTIR from Figure 4.1 and GCFID analyses from Figures 4.6 to 4.9.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 shows HC emissions of 0.064 g/kWh and 0.066 g/kWh, respectively. HC emissions were reduced almost the same for B10, reduced 25.0% to 0.048 g/kWh and 24.2% to 0.05 g/kWh for both loads. Plastic-derived fuels consistently increased by 12.5% to 0.072 g/kWh at 1 Nm, later increased by 15.2% to 0.076 g/kWh for HDPE10 and 12.5% to 0.072 g/kWh and 21.2% to 0.08 g/kWh for PP10. This confirms that B10 performs efficiently, while plastic-derived fuels may not be sufficient to atomize well under high-load conditions. This is attributed to the limited oxidation of longer-chain hydrocarbons from plastic-derived fuels under high-load and maximum load conditions. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 recorded HC emissions by 0.050 g/kWh and 0.052 g/kWh, respectively. B10 again performed well with a reduction by 48.0% to 0.026 g/kWh and 38.5% to 0.032 g/kWh. HDPE10 shows a high increment of HC emissions by 24.0% to 0.062 g/kWh and 30.8% to 0.068 g/kWh, while PP10% slightly increased by 4.0% to 0.052 g/kWh and 3.9% to 0.054 g/kWh, respectively. PP10 has comparatively better high-load adaptability compared to HDPE10.

HC emissions were closely related to the fuel's viscosity for the atomization process. A finer and consistent spray pattern may form with lower fuel viscosity to atomize well, thus mixing with air and promoting more complete combustion, resulting in lower HC emissions formation, as supported by Arumugam *et al.* (2024), Fayad *et al.* (2021), and Haq *et al.* (2024). A certain specific viscosity may occasionally enhance injection performance and combustion control, which lowers HC emissions. The oxygenated nature of B10 compensates for its lower calorific value by achieving significant reductions in HC emissions (Reksowardojo *et al.*, 2020; Singh *et al.*, 2021). In contrast, HDPE10 and PP10 with lower calorific values show higher

emissions due to incomplete combustion. Plastic-derived HDPE10 fuel, with its higher density and viscosity, impairs atomization and mixing. This leads to incomplete combustion and thus elevated HC emissions. On the other hand, PP10 with lower viscosity achieves better spray formation, leading to relatively lower HC emissions (Mangesh *et al.*, 2020; Pumpuang *et al.*, 2024). As confirmed by CHNS analysis from Figure 4.10, the oxygen content in B10 facilitates more complete combustion, hence reducing HC emissions. HDPE10 and PP10 lack oxygenated functional groups contributing to their higher HC emissions (Avinash *et al.*, 2019; Dutta & Gupta, 2021).

B10 consistently demonstrates lower HC emissions due to its oxygenated nature, which enhances oxidation and reduces unburned hydrocarbons. HDPE10 and PP10 exhibit higher HC emissions, primarily due to lower density, lower viscosity, and long-chain hydrocarbon structures. PP10 generally performs better than HDPE10 due to improved atomization and combustion characteristics. Although this study did not exceed permissible HC thresholds, the elevated HC emissions from HDPE10 and PP10 at high loads attract attention for emission compliance.

4.3.4 NO_x Emissions

Figure 4.17 and Table 4.14 display NO_x emissions produced from the combustion process of the diesel engine under varying parameters. The findings illustrate the influence of fuel composition and operating conditions on NO_x formation. According to the Euro V standard, the NO_x limit for non-road diesel engines with power less than 19 kW is approximately 5.0 g/kWh. The trend shows the NO_x emissions increasing as loads increase. The pattern at higher speed shows that the emitted NO_x emissions are almost identical to each other. The trend shows a reduction pattern of NO_x emissions as the in-cylinder temperature increases. During 2000 rpm and 2500 rpm, B10 shows NO_x emissions deviation range from -31.9% to -16.9% and -16.0% to +1.4%, HDPE between -30.4% to -10.6%, and PP1- between -23.2% to -8.5% and -21.0% to -3.3%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 shows NO_x emissions by 0.46 g/kWh and 0.68 g/kWh corresponding to in-cylinder temperatures of 1709.0 K and 1852.7 K, respectively. B10 emits NO_x

emissions reduced by 31.8% to 0.31 g/kWh and 17.5% to 0.56 g/kWh corresponding to in-cylinder temperatures of 1699.6 K and 1880.1 K, respectively. HDPE10 shows NO_x reduction by 30.4% to 0.32 g/kWh and 15.5% to 0.58 g/kWh corresponding to in-cylinder temperatures of 1650.7 K and 1892.3 K, respectively. PP10 shows NO_x reduction by 23.2% to 0.35 g/kWh and 9.7% to 0.62 g/kWh corresponding to in-cylinder temperatures of 1785.3 K and 1888.2 K, respectively. B10 and HDPE10 show lower in-cylinder temperatures, suggesting slower combustion, which aligns with lower NO_x emissions. PP10 showed modest NO_x emissions reduction at a modest rate, with the highest in-cylinder temperature possibly due to local oxygen deficiencies.

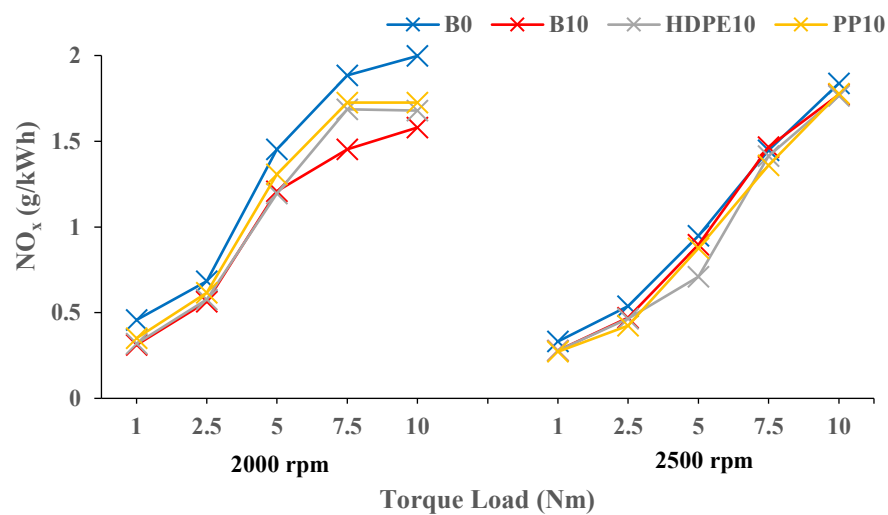


Figure 4.17 Variation of NO_x exhaust emissions in different loads and speeds

Table 4.14 Summary of NO_x emissions of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (g/kWh)	Max In- cylinder Temperature for B0 (K)	B10 (g/kWh)	Max In- cylinder Temperature for B10 (K)	HDPE10 (g/kWh)	Max In-cylinder Temperature for HDPE10 (K)	PP10 (g/kWh)	Max In-cylinder Temperature for PP10 (K)
2000	1	0.46	1709.0	0.31 (-31.9*)	1699.6	0.32 (-30.4*)	1650.7	0.35 (-23.2*)	1785.3
	2.5	0.68	1852.7	0.56 (-17.5*)	1880.1	0.58 (-15.5*)	1892.3	0.62 (-9.7*)	1888.2
	5	1.45	2022.6	1.21 (-16.9*)	1956.2	1.19 (-17.8*)	1989.1	1.32 (-10.1*)	2036.7
	7.5	1.89	2199.1	1.45 (-22.9*)	2098.0	1.69 (-10.6*)	2128.3	1.73 (-8.5*)	2159.1
	10	2.00	2259.3	1.58 (-20.9*)	2183.3	1.68 (-16.0*)	2088.3	1.73 (-13.6*)	2162.5
2500	1	0.33	1682.3	0.28 (-16.0*)	1686.8	0.28 (-16.0*)	1678.4	0.27 (-18.0*)	1626.3
	2.5	0.54	1891.3	0.47 (-12.4*)	1754.9	0.47 (-13.6*)	1753.7	0.43 (-21.0*)	1787.2
	5	0.95	2056.0	0.90 (-5.6*)	1935.2	0.71 (-25.2*)	1869.4	0.88 (-7.7*)	1982.4
	7.5	1.45	2103.7	1.47 (+1.4*)	2134.1	1.41 (-2.3*)	2057.5	1.36 (-6.0*)	2069.9
	10	1.84	2213.4	1.77 (-3.6*)	2213.4	1.77 (-4.0*)	2286.5	1.78 (-3.3*)	2238.0

*The values in parentheses represent the deviation% increase (+) or decrease (-) in NO_x relative to B0

At 2500 rpm and low loads (1 Nm and 2.5 Nm), B0 displays NO_x emissions of 0.33 g/kWh and 0.54 g/kWh corresponding to in-cylinder temperatures 1682.3 K and 1891.3 K, respectively. B10 generated less NO_x emissions by 16.0% to 0.28 g/kWh and 12.4% to 0.47 g/kWh corresponding to in-cylinder temperatures 1686.8 K and 1754.9 K, respectively. HDPE10 shows NO_x emissions reduced by 16.0% to 0.28 g/kWh and 13.6% to 0.47 g/kWh corresponding to in-cylinder temperatures 1678.4 K and 1753.7 K, respectively. PP10 shows modest NO_x reduction by 18.0% to 0.27 g/kWh and 21.9% to 0.43 g/kWh corresponding to in-cylinder temperatures of 1626.3 K and 1787.2 K, respectively. Among the alternative fuels, PP10 showed higher NO_x emissions reduction, and all fuels overcame NO_x formation under light loads and high-speed conditions.

At 2000 rpm and medium load (5 Nm), B0 shows NO_x emissions of 1.45 g/kWh corresponding in-cylinder temperature of 2022.6 K. B10 shows reduction of NO_x emissions by 16.9% to 1.21 g/kWh corresponding in-cylinder temperature 1956.2 K. HDPE10 and PP10 show NO_x reduction by 17.8% to 1.19 g/kWh and 10.1% to 1.31 g/kWh corresponding in-cylinder temperature 1989.1 K and 2036.7 K, respectively. PP10 produces the highest in-cylinder temperature, and slightly higher than B0, the NO_x reduction is the lowest. This might be due to the fuel composition structure, which has led to partial reduction of NO_x via delayed ignition. At 2500 rpm and medium load (5 Nm), B0 produces NO_x emissions by 0.95 g/kWh. HDPE10 reduces the highest NO_x emissions by 25.2% to 0.71 g/kWh corresponding in-cylinder temperature of 1869.4 K, while B10 and PP10 show a slight reduction to 5.6% to 0.90 g/kWh and 7.7% to 0.88 g/kWh corresponding to in-cylinder temperatures of 1935.2 K and 1982.4 K, respectively. HDPE10 with larger NO_x emissions reduction, with the corresponding lowest in-cylinder temperature, appears to benefit in medium load and high speed conditions.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 shows NO_x emissions of 1.89 g/kWh and 2.0 g/kWh corresponding to in-cylinder temperatures 2199.1 K and 2259.3 K, respectively. B10 shows the highest NO_x emissions reduction by 22.9% to 1.45 g/kWh and 20.9% to 1.58 g/kWh corresponding to in-cylinder temperature 2098.0 K and 2183.3 K, respectively. HDPE10 shows NO_x emissions reduction by 10.6% to

1.69 g/kWh and 16.0% to 1.68 g/kWh, corresponding to in-cylinder temperature 2128.3 K and 2088.3 K, respectively. While PP10 shows NO_x emissions reduction by 8.5% to 1.73 g/kWh and 13.6% to 1.73 g/kWh with corresponding in-cylinder temperature 2159.1 K and 2162.5 K, respectively. B10 achieved noticeably lower combustion temperatures than B0, validating the temperature-mitigation effect due to the higher calorific value from Figure 4.2 and oxygenated structure. At 2500 rpm and high loads (7.5 Nm and 10 Nm), B0 shows NO_x emissions by 1.45 g/kWh and 1.84 g/kWh corresponding to in-cylinder temperatures of 2103.7 K and 2213.4 K, respectively. B10 shows slightly increased NO_x emissions emitted by 1.4% to 1.47 g/kWh and reduced 3.6% to 1.77 g/kWh corresponding to in-cylinder temperature 2134.1 K and 2213.4 K, respectively. HDPE10 shows NO_x emissions reduction by 2.3% to 1.41 g/kWh and 4.0% to 1.77 g/kWh corresponding to in-cylinder temperature 2057.5 K and 2286.5 K, respectively. PP10 shows NO_x emissions reduction by 6.0% to 1.36 g/kWh and 3.3% to 1.78 g/kWh corresponding to in-cylinder temperature 2069.9 K and 2238.0 K, respectively. These high-load results show that as the load increases, the influence of fuel chemistry declines, and NO_x emissions become the dominant mechanism, thereby limiting the ability of alternative fuels to further reduce NO_x emissions.

The observed NO_x emission trends in this study deviate from conventional theoretical expectations. Combustion theory suggests that a higher oxygen content in the fuel promotes more complete combustion, which elevates the in-cylinder temperature. This temperature rise is expected to enhance thermal NO_x formation through the Zeldovich mechanism, leading to increased NO_x emissions due to intensified thermal conditions within the combustion chamber. However, the experimental results indicate a different trend, suggesting that other influencing factors may be moderating NO_x formation despite higher oxygen availability (Ahmad Saad *et al.*, 2023; Ghany *et al.*, 2024; Pimenidou *et al.*, 2019). The observed NO_x trends are strongly influenced by fuel physicochemical properties, such as viscosity, density, calorific value, and oxygen content. Lower viscosity fuels generally enhance spray atomization and air-fuel mixing, resulting in more uniform combustion and reduced peak flame temperatures, thereby restraining NO_x formation (Fayad *et al.*, 2021; Horvat *et al.*, 2021; Sayyed *et al.*, 2021). Conversely, higher viscosity contributes to

poor atomization and localized rich zones, which elevate combustion temperatures and promote NO_x generation (Das & Chowdhury, 2023; Horvat *et al.*, 2021; Kumar *et al.*, 2019). The oxygenated structure of biodiesel significantly improves combustion efficiency and supports lower NO_x emissions, particularly at low and medium loads. In contrast, plastic-derived fuels display mixed results due to their unique molecular composition (Faisal *et al.*, 2023; Januszewicz *et al.*, 2023). Their faster evaporation rates and favourable volatility enhance air-fuel mixing, especially at low loads, resulting in effective NO_x reduction. However, at higher loads, the dominance of thermal NO_x formation mechanisms limits the overall reduction potential.

In conclusion, fuel density and calorific value play critical roles in shaping combustion dynamics. Higher density fuels may lead to locally rich mixtures, increasing combustion temperature and NO_x emissions. Fuels with greater calorific values, such as PP10, release more thermal energy per unit mass, potentially elevating in-cylinder temperatures and exacerbating NO_x formation unless counteracted by superior atomization or combustion control (Liu *et al.*, 2022; Paykani *et al.*, 2022). In summary, alternative fuels consistently demonstrated superior NO_x emissions reduction due to their calorific value, viscosity, and density, as supported by Figures 4.2 to 4.4, respectively.

4.3.5 O₂ Production

The O₂ production from the diesel engine combustion process is shown in Figure 4.18 and Table 4.15. Lower O₂ production indicates more complete combustion, while higher levels suggest incomplete combustion or excess air. The trend shows the O₂ production reduced as the load increases for all fuel blends. The trends show the fluctuation rate of less than 4.1% for all alternative fuels. During 2000 rpm and 2500 rpm, B10 shows O₂ production deviation from -1.5% to +0.5% and -3.3% to +1.0%, HDPE10 between -2.9% to +0.2% and -4.1% to -0.3%, and PP10 between -1.6% to +3.8% and -0.2% to +1.5%, respectively. At 2000 rpm and low loads (1 Nm and 2.5 Nm), B0 shows O₂ production by 726.5 g/kWh and 693.7 g/kWh, respectively. B10 shows slightly reduced O₂ production by 0.7% to 721.2 g/kWh and

1.5% to 683.6 g/kWh. HDPE10 shows O₂ production reduced by 0.2% to 727.8 g/kWh and 1.0% to 686.7 g/kWh, while PP10 shows a constant value of 726.5 g/kWh and is reduced by 1.6% to 682.6 g/kWh, respectively. At 2500 rpm and low loads (1 Nm and 2.5 Nm), B0 shows O₂ production by 728.6 g/kWh and 688.0 g/kWh, respectively. B10 shows O₂ production slightly reduced to 0.4% to 725.7 g/kWh and increased by 1.0% to 694.5 g/kWh, while PP10 shows a slight reduction of O₂ production by 0.2% to 727.4 g/kWh and 0.2% to 686.3 g/kWh, respectively. These slight differences at low engine loads suggest lower combustion intensities and lower in-cylinder temperatures.

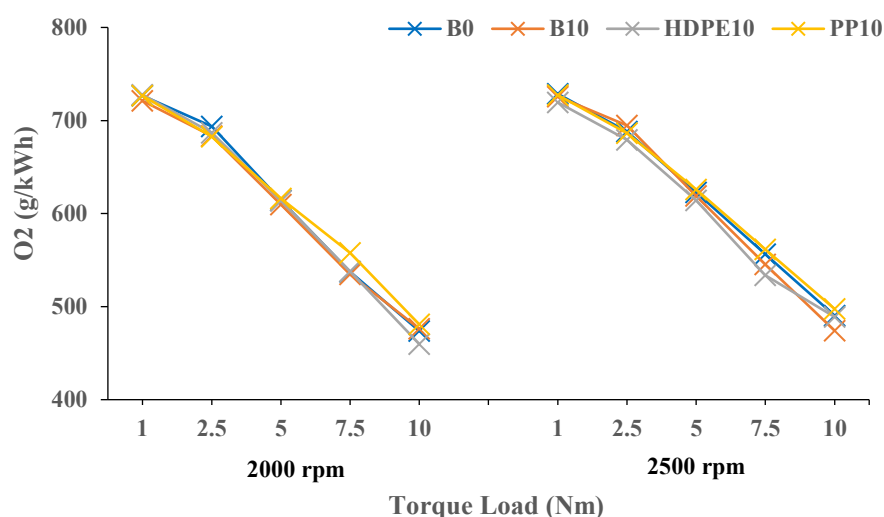


Figure 4.18 Variation of O₂ production of diesel blends at different loads and speeds

Table 4.15 Summary of O₂ production of diesel blends in the variation parameter

Speed (rpm)	Torque Load (Nm)	B0 (g/kWh)	B10 (g/kWh)	HDPE10 (g/kWh)	PP10 (g/kWh)
2000	1	726.5	721.2 (-0.7*)	727.8 (+0.2*)	726.5 (constant*)
	2.5	693.7	683.5 (-1.5*)	686.7 (-1.0*)	682.6 (-1.6*)
	5	614.1	609.6 (-0.7*)	613.7 (-0.1*)	616.2 (+0.3*)
	7.5	537.4	534.5 (-0.5*)	537.8 (+0.1*)	557.9 (+3.8*)
	10	473.8	476.3 (+0.5*)	459.9 (-2.9*)	480.9 (+1.5*)
2500	1	728.6	725.7 (-0.4*)	719.6 (-1.2*)	727.4 (-0.2*)
	2.5	688.0	694.5 (+1.0*)	679.4 (-1.3*)	686.3 (-0.2*)
	5	622.7	619.0 (-0.6*)	614.1 (-1.4*)	626.0 (+0.5*)
	7.5	556.3	545.2 (-2.0*)	533.7 (-4.1*)	561.6 (+1.0*)

10	490.2	474.2 (-3.3*)	489.0 (-0.3*)	497.6 (+1.5*)
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*The values in parentheses represent the deviation% increase (+) or decrease (-) in O₂ relative to B0

At 2000 rpm and medium load (5 Nm), B0 displays O₂ production by 614.1 g/kWh. B10 and HDPE show a slight reduction by 0.7% to 609.6 g/kWh and 0.1% to 613.7 g/kWh, while PP10 shows a slight increase by 0.3% to 616.2 g/kWh, respectively. At 2500 rpm and medium load (5 Nm), B0 displays O₂ production by 622.7 g/kWh. B10 and HDPE10 show O₂ production slightly reduced by 0.6% to 619.0 g/kWh and 1.4% to 614.1 g/kWh, while PP10 shows a slight increase of 0.5% to 626.0 g/kWh. It can be concluded that PP10 slightly lessens combustion efficiency under medium load conditions due to less reactive components in the plastic-derived fuel. HDPE10 may enhance combustion efficiency under medium load conditions, possibly due to better AF mixing.

At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 emits O₂ production by 537.4 g/kWh and 473.8 g/kWh, respectively. B10 fluctuated O₂ production by 0.5% less to 534.5 g/kWh and 0.5% more to 476.3 g/kWh, respectively. HDPE10 also shows the same pattern as B10, with O₂ producing 0.1% more to 537.8% and 2.9% less to 459.9 g/kWh as loads increase. PP10 shows increased O₂ production by 3.8% to 557.9 g/kWh and 1.5% to 480.9 g/kWh, respectively. HDPE10 shows the lowest O₂ production, indicating more complete combustion, while PP10 shows higher indicate less efficient combustion. At 2000 rpm and high loads (7.5 Nm and 10 Nm), B0 displays O₂ production by 556.3 g/kWh and 490.2 g/kWh, respectively. B10 and HDPE10 show a reduction in O₂ production by 2.0% to 545.2 g/kWh and 3.3% to 474.2 g/kWh, and 4.1% to 533.7 g/kWh and 0.3% to 489.0 g/kWh, respectively. O₂ production from PP10 was slightly increased to 1.0% to 561.6 g/kWh and 1.5% to 497.6 g/kWh, respectively. These findings revealed that PP10 may hinder oxygen oxidation due to less favourable combustion properties.

Reduction of O₂ production suggests that more oxygen is being consumed in combustion, potentially leading to variation in CO, CO₂, HC, and NO_x emissions. Biodiesel generally results in lower CO emissions due to its oxygenated nature, which enhances combustion efficiency. However, plastic-derived fuels may exhibit slightly higher CO emissions due to poorer atomization and incomplete oxidation under certain

conditions (Januszewicz *et al.*, 2023; Pumpuang *et al.*, 2024; Singh *et al.*, 2020). CO₂ emissions are a direct indicator of complete combustion, indicating that higher CO₂ emissions mean better oxidation of carbon-based fuels. Since B10 exhibits lower O₂ production in most conditions, it suggests that more oxygen is being used in combustion, likely leading to higher CO₂ emissions. HDPE10 also shows a similar pattern to B10. However, it emits CO₂ emissions lower than B10 in all engine speeds and loads. PP10 shows irregular increases in O₂ production, indicating less complete combustion at lower engine speeds, which leads to lower CO₂ emissions in those conditions. However, PP10 exhibits higher CO₂ emissions at higher engine speeds, suggesting improved combustion efficiency (Ilmi *et al.*, 2024; Singh *et al.*, 2020).

HC emissions are a result of incomplete combustion, often due to fuel-rich conditions, lower oxygen availability, or poor atomization. Lower HC emissions from B10 suggest better fuel oxidation due to its oxygenated nature, while HDPE10 and PP10 exhibit higher HC emissions due to their plastic-derived composition, which lacks oxygenated functional groups (Mehanathan *et al.*, 2025; Modi & Patel, 2023; Yusuf *et al.*, 2023). B10 generally results in higher NO_x emissions due to its oxygenated nature, which increases combustion temperature. Plastic-derived fuels may exhibit moderate NO_x emissions, depending on combustion efficiency and temperature variations. Despite the theoretical expectation of NO_x emissions formation, the experimental results show that the alternative fuels with high inherent oxygen content can produce lower NO_x emissions. The factors, such as lower calorific values, altered ignition delays, and heat release rates, can moderate the combustion temperature (Ahmad Saad *et al.*, 2023; Ghany *et al.*, 2024; Pimenidou *et al.*, 2019). This causes limiting NO_x formation even in the presence of an abundance of oxygen.

O₂ production can be used as an indicator to evaluate the AF ratio during combustion. An optimal AF ratio is produced by an ideal AF ratio. Excessive or insufficient oxygen levels may indicate an unbalanced AF mixture, which can affect the efficiency of combustion (Haq *et al.*, 2024; Wang *et al.*, 2021). Low O₂ production suggests that more oxygen is being utilized in combustion, which often occurs in fuel-lean conditions where excess air is available. Fuel-lean combustion typically leads to more complete oxidation of hydrocarbons, resulting in lower HC and CO emissions.

This led to efficient combustion with fewer HC and CO emissions discharged (Dimitriou *et al.*, 2020; Ogunkunle & Ahmed, 2021; Haq *et al.*, 2024). Variations in O₂ production under different engine speeds and loads provide insight into the engine's response to varying conditions. Significant deviations may indicate issues with air intake, fuel injection, or combustion efficiency, potentially affecting performance and emissions (Song *et al.*, 2016; Sun *et al.*, 2021; Wang *et al.*, 2021).

4.4 MLP Models Training

This study utilizes a feed-forward backpropagation MLP network to establish the relationship between input parameters from exhaust emissions and engine performance to predict NO_x emissions. The MLP model is selected for its proven ability to model complex and nonlinear relationships, making it ideal for capturing the complex interactions within diesel engine operations. A critical step in developing the MLP model is determining the optimal number of neurons in the hidden layer, as this significantly affects the accuracy and performance of the model. To achieve this, the simulation using MATLAB R2024b explores configurations with hidden layer neurons ranging from 1 to 19. A widely accepted guideline suggests that the number of neurons in the hidden layer is 18 neurons, which should not be more than twice the 9th input parameter (Deng, 2023; Rajawat & Jain, 2020). However, extending this range slightly to 19 neurons ensures that the optimal configuration is not prematurely constrained, allowing the model to capture more intricate patterns in the dataset. If the hidden layer contains too few neurons, the model may lack the necessary capacity to learn the complex relationships governing NO_x emissions, leading to underfitting. Conversely, an excessively large number of neurons increases model complexity, which may result in overfitting, where the model learns noise rather than meaningful trends. To mitigate these issues, training the model with neuron counts to 19 allows for empirical evaluation of the best balance between model complexity and generalization (Ali *et al.*, 2023; Ali *et al.*, 2024).

The relative significance of each input parameter in predicting NO_x emissions was assessed based on the trained MLP models. The models incorporated nine input

variables: engine speed, torque, power output, BSFC, fuel flow rate, and exhaust emissions, including CO, CO₂, O₂, and HC emissions. The target output was the NO_x emissions concentration. Among these, O₂ production, torque, and HC emissions were consistently identified as the most influential parameters. The torque reflects engine load and directly influences in-cylinder temperatures, which are critical to NO_x formation. O₂ production represents the AF ratio and combustion efficiency; lower O₂ levels in the exhaust typically indicate more complete combustion and higher combustion temperatures, promoting NO_x formation. HC emissions generally exhibit an inverse relationship with NO_x; lower HC levels suggest more efficient combustion, which often correlates with increased NO_x. Engine speed and power output showed a moderate influence as they affect combustion timing and airflow dynamics. The importance of CO and CO₂ varied depending on the fuel type, reflecting their indirect relationship with combustion completeness and oxygen availability. In contrast, BSFC and fuel flow rate had a relatively low influence across most models, indicating their secondary role in NO_x prediction.

The optimum configuration of the models is represented by having different training neurons in the hidden layer. This variation of different neurons in the hidden layer is important as it is not considered fixed by a certain rule. The prediction accuracy was enhanced by having a higher number of neurons in the hidden layer since the NO_x emissions interact in a nonlinear behaviour between the engine parameters (Adil *et al.*, 2022; Khan *et al.*, 2024). By testing neuron counts to 19, the study establishes a benchmark to determine whether the optimal number lies within the suggested range or if additional neurons provide further improvements. If performance stabilizes before reaching 19 neurons, adding more neurons would be unnecessary, ensuring computational efficiency without compromising prediction accuracy. This structured approach ensures that the MLP model is optimized based on empirical evidence rather than arbitrary selection, providing a reliable foundation for predicting NO_x emissions (Li *et al.*, 2017; Wang *et al.*, 2024).

As part of the analysis, box-and-whisker plots in Figures 4.19 to 4.28 are employed to visualize the distribution of the dataset and data cleaning for the training algorithm. These plots effectively highlight key statistical features, such as the median,

spread, and potential outliers, offering valuable insights into the variability and structure of the input and output parameters. Complementing this, descriptive statistics presented in Tables 4.16 to 4.25 summarize the key data attributes, including mean, standard deviation, and range, providing a comprehensive understanding of the dataset. These tools serve to enhance data transparency and ensure informed decisions during model training. They not only establish a solid foundation for the training of the MLP network but also validate its ability to predict NO_x emissions with accuracy and reliability.

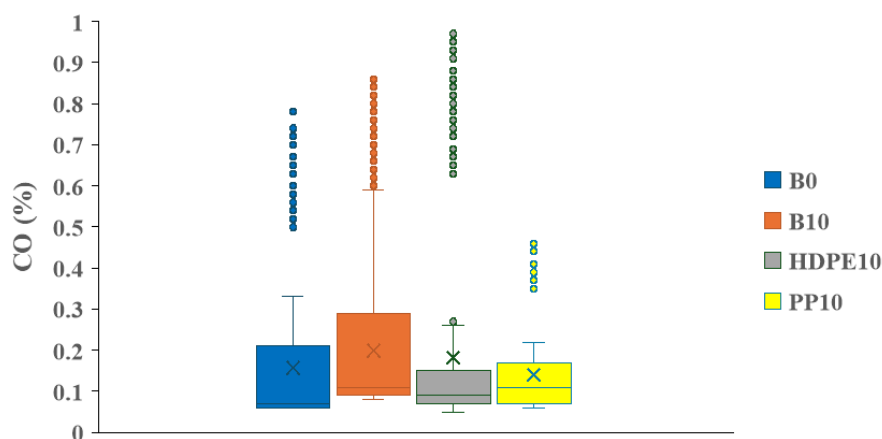
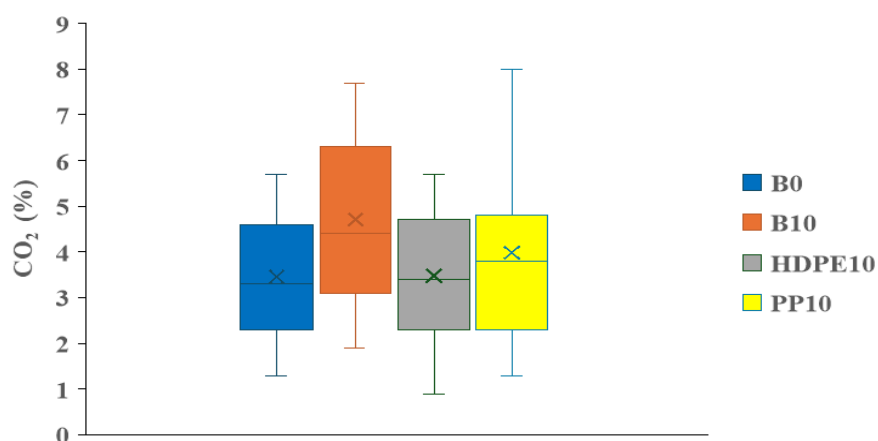


Figure 4.19 Boxplot for CO emissions

Table 4.16 Descriptive statistics for CO emissions

	B0	B10	HDPE10	PP10
Min	0.06	0.08	0.05	0.06
Max	0.79	0.87	0.98	0.46
R	0.73	0.79	0.93	0.4
Sum	142.17	179.33	163.59	126.92
$\bar{x}$	0.158	0.199	0.182	0.141
Median	0.07	0.11	0.09	0.11
σ	0.155	0.18	0.231	0.088
σ^2	0.024	0.033	0.053	0.008
MR	0.425	0.475	0.515	0.26
Quartile	Q1	0.06	0.09	0.07
	Q2	0.07	0.11	0.11
	Q3	0.21	0.29	0.17
IQR	0.15	0.2	0.08	0.1
Outliers	0.5 and above (90 points)	0.6 and above (48 points)	0.27 and above (142 points)	0.35 and above (90 points)
<i>CV</i>	0.98	0.906	1.271	0.623

Figure 4.20 Boxplot for CO₂ emissionsTable 4.17 Descriptive statistics for CO₂ emissions

		B0	B10	HDPE10	PP10
Min		1.3	1.9	0.9	1.3
Max		5.7	7.7	5.7	8
R		4.4	5.8	4.8	6.7
Sum		3114.8	4243.4	3129.2	3591.6
$\bar{x}$		3.461	4.715	3.477	3.991
Median		3.3	4.4	3.4	3.8
σ		1.403	1.798	1.445	4.1
σ^2		1.97	3.235	2.102	1.844
MR		3.5	4.8	3.3	3.399
Quartile	Q1	2.3	3.1	2.3	4.65
	Q2	3.3	4.4	3.4	2.3
	Q3	4.6	6.3	4.7	3.8
IQR		2.3	3.2	2.4	4.8
Outliers		none	none	none	none
<i>CV</i>		0.406	0.381	0.417	0.462

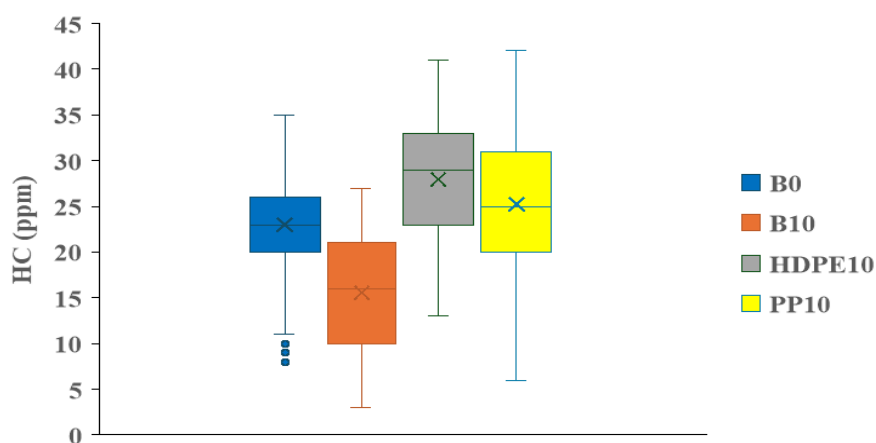
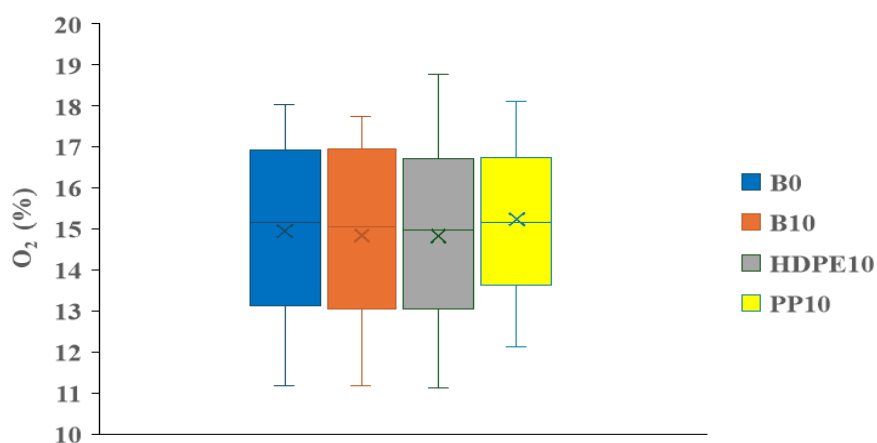


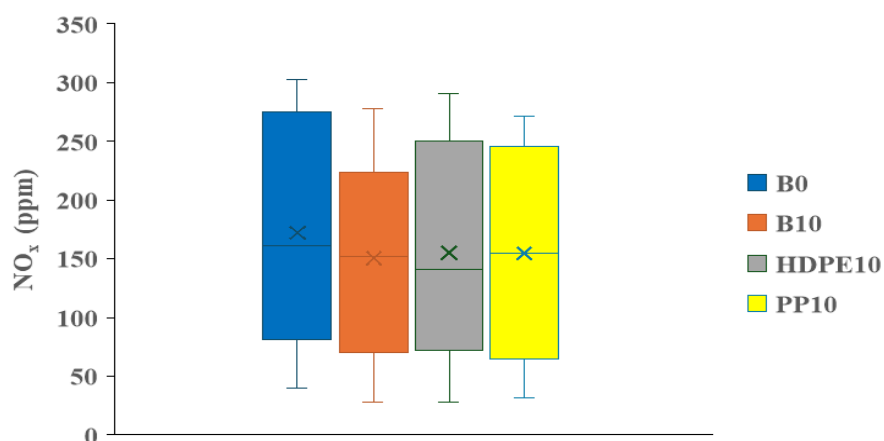
Figure 4.21 Boxplot for HC emissions

Table 4.18 Descriptive statistics for HC emissions

	B0	B10	HDPE10	PP10
Min	8	3	13	6
Max	35	27	41	42
R	27	24	28	36
Sum	20726	14032	25139	22716
$\bar{x}$	23.029	15.591	27.932	25.24
Median	23	16	29	25
σ	6.016	6.365	6.696	8.0415
σ^2	36.193	41.511	44.837	64.665
MR	21.5	15	27	24
Quartile	Q1	20	10	23
	Q2	23	16	29
	Q3	26	21	33
IQR	6	11	10	11
Outliers	10 and below (39 points)	none	none	none
<i>CV</i>	0.261	0.408	0.24	0.319

Figure 4.22 Boxplot for O₂ productionTable 4.19 Descriptive statistics for O₂ productions

	B0	B10	HDPE10	PP10
Min	11.17	11.19	11.13	12.12
Max	18.04	17.73	18.77	18.1
R	6.87	6.54	7.64	5.98
Sum	13453.74	13354.04	13341.55	13708.7
$\bar{x}$	14.949	14.838	14.824	15.232
Median	15.17	15.04	14.98	15.145
σ	2.229	2.274	2.247	1.854
σ^2	4.97	5.171	5.05	3.438
MR	14.605	14.46	14.95	15.11
Quartile	Q1	13.12	13.05	13.63
	Q2	15.17	15.04	15.145
	Q3	16.93	16.7	16.73
IQR	3.81	3.9	3.65	3.1
Outliers	none	none	none	none
<i>CV</i>	0.149	0.153	0.152	0.122

Figure 4.23 Boxplot for NO_x emissionsTable 4.20 Descriptive statistics for NO_x emissions

	B0	B10	HDPE10	PP10
Min	40	28	28	32
Max	302	278	290	271
R	262	250	262	239
Sum	154767	135241	139672	139244
$\bar{x}$	171.963	150.268	155.191	154.716
Median	161	151.5	140.5	155
σ	90.311	81.879	86.839	84.781
σ^2	8156.062	6704.165	7541.078	7187.875
MR	171	153	159	151.5
Quartile	Q1	81	70	72
	Q2	161	151.5	140.5
	Q3	274.5	223	250
IQR	193.5	153	178	181
Outliers	none	none	none	none
CV	0.525	0.545	0.56	0.548

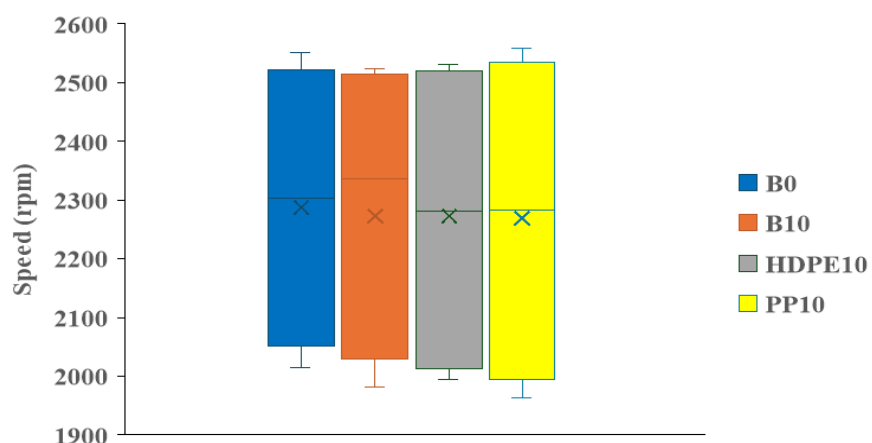


Figure 4.24 Boxplot for speed

Table 4.21 Descriptive statistics for speed

	B0	B10	HDPE10	PP10
Min	2014.595	1981.126	1994.363	1962.998
Max	2550.074	2523.05	2530.98	2557.79
R	535.479	541.924	536.617	594.792
Sum	2058889.3	2045438	2045487	2042263
$\bar{x}$	2287.655	2272.708	2272.763	2269.181
Median	2302.445	2335.738	2281.481	2282.484
σ	234.748	240.959	245.533	262.2706
σ^2	55106.424	58061.4	60286.52	68785.9
MR	2282.335	2252.088	2262.672	2260.394
Quartile	Q1 2050.529	2029.875	2012.658	1994.777
	Q2 2302.445	2335.738	2281.481	2282.484
	Q3 2521.186	2513.289	2518.716	2534.234
IQR	470.657	483.414	506.0585	539.457
Outliers	none	none	none	none
CV	0.103	0.106	0.108	0.116

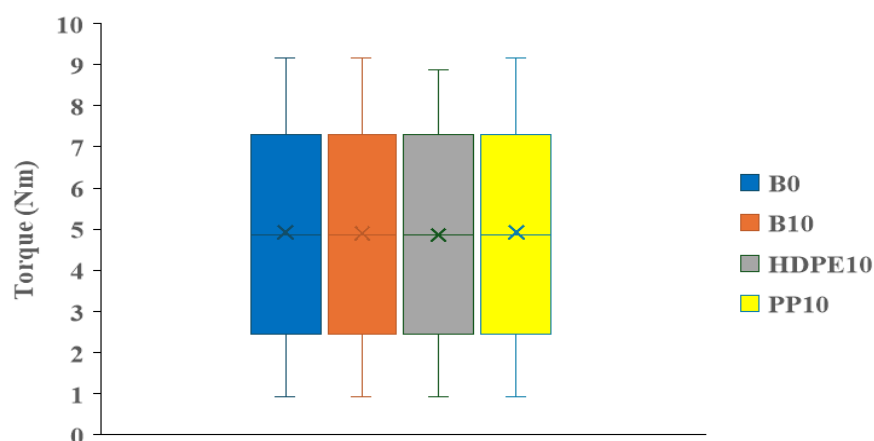


Figure 4.25 Boxplot for torque

Table 4.22 Descriptive statistics for torque

	B0	B10	HDPE10	PP10
Min	0.937	0.931	0.935	0.932
Max	9.155	9.155	8.876	9.165
R	8.218	8.224	7.941	8.233
Sum	4434.198	4407.97	4380.917	4434.044
$\bar{x}$	4.927	4.898	4.868	4.927
Median	4.867	4.865	4.867	4.863
σ	2.988	2.948	2.906	2.988
σ^2	8.926	8.688	8.446	8.926
MR	5.046	5.043	4.905	5.048
Quartile	Q1	2.447	2.441	2.447
	Q2	4.867	4.867	4.863
	Q3	7.293	7.299	7.288
IQR	4.845	4.851	4.858	4.841
Outliers	none	none	none	none
CV	0.606	0.602	0.597	0.606

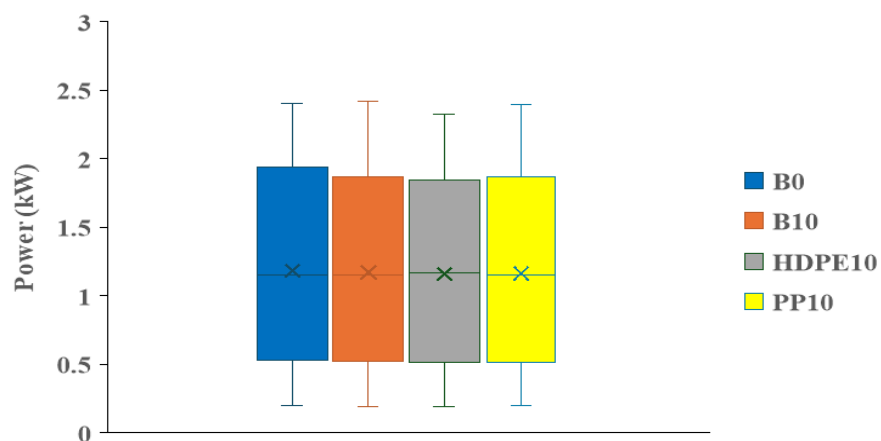


Figure 4.26 Boxplot for power

Table 4.23 Descriptive statistics for power

	B0	B10	HDPE10	PP10
Min	0.199	0.195	0.196	0.201
Max	2.399	2.415	2.322	2.397
R	2.2	2.2195	2.126	2.196
Sum	1064.96	1053.785	1043.179	1048.562
$\bar{x}$	1.183	1.171	1.159	1.165
Median	1.155	1.154	1.171	1.155
σ	0.733	0.724	0.704	0.717
σ^2	0.537	0.524	0.496	0.515
MR	1.3	1.305	1.259	1.299
Quartile	Q1	0.527	0.523	0.517
	Q2	1.155	1.154	1.171
	Q3	1.942	1.872	1.847
IQR	1.414	1.349	1.33	1.354
Outliers	none	none	none	none
CV	0.62	0.618	0.608	0.616

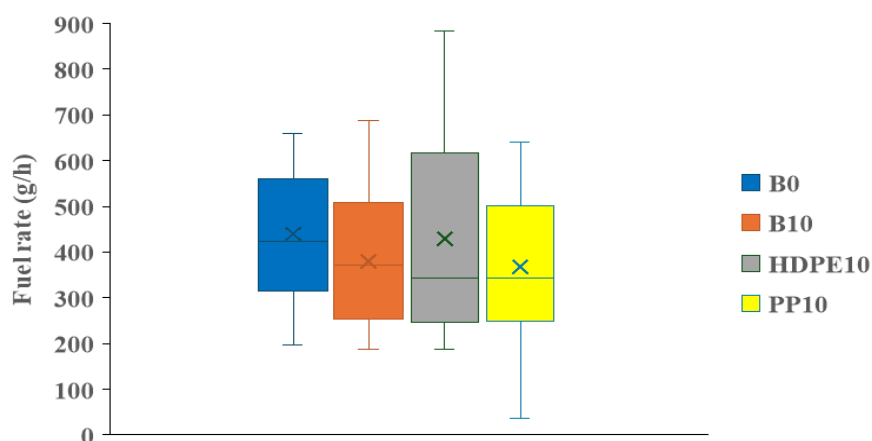


Figure 4.27 Boxplot for fuel rate

Table 4.24 Descriptive statistics for fuel rate

	B0	B10	HDPE10	PP10
Min	196.259	186.673	186.673	37.512
Max	659.437	687.284	882.716	640.447
R	463.178	500.611	696.043	602.935
Sum	396442.75	341852.6	386448.5	331330.1
$\bar{x}$	440.492	379.836	429.387	368.145
Median	423.049	371.702	343.942	343.682
σ	139.54	135.158	204.985	143.137
σ^2	19471.302	18267.81	42018.7	20488.14
MR	427.848	436.979	534.695	338.979
Quartile	Q1 316.389	254.505	246.555	250.206
	Q2 423.049	371.702	343.942	343.682
	Q3 560.294	509.07	616.135	501.185
IQR	243.905	254.566	369.58	250.979
Outliers	none	none	none	none
CV	0.317	0.356	0.477	0.389

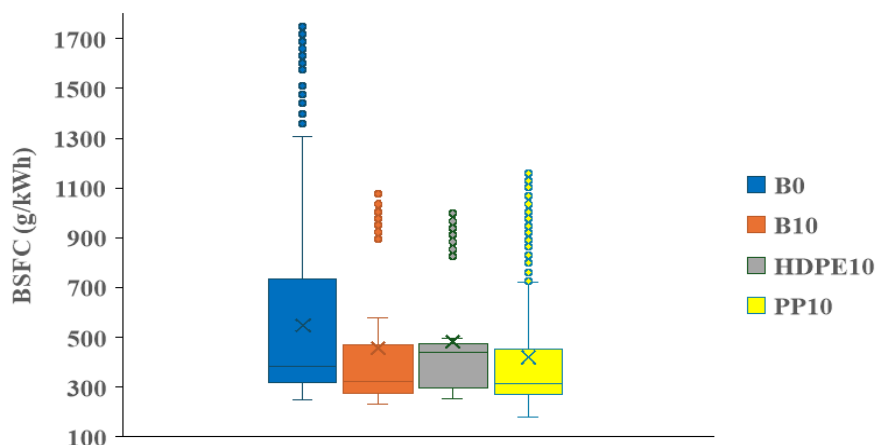


Figure 4.28 Boxplot for BSFC

Table 4.25 Descriptive statistics for BSFC

	B0	B10	HDPE10	PP10
Min	247.599	230.907	252.191	182.237
Max	1755.48	1079.883	1020.714	1165.416
R	1507.88	848.976	768.523	983.179
Sum	493829.689	411164.7	434613.1	378088.9
$\bar{x}$	548.7	456.85	482.903	420.099
Median	383.725	322.517	439.315	312.374
σ	369.914	265.869	245.168	231.432
σ^2	136836.11	70686.51	60107.26	53560.86
MR	1001.539	655.395	636.453	673.826
Quartile	Q1 316.998	273.987	295.195	271.338
	Q2 383.725	322.517	439.315	312.374
	Q3 733.405	472.339	473.498	452.409
IQR	416.407	198.351	178.304	181.071
Outliers	above 1358.375 (64 points)	above 893.66 (179 points)	above 826.092 (179 points)	above 725.602 (130 points)
CV	0.674	0.582	0.508	0.551

The range (R) of emissions and performance parameters provides valuable information on the variability of different fuel blends. For emissions, CO exhibits moderate ranges of 4.4–6.7 %, indicating variability in incomplete combustion across the blends. CO₂ with slightly larger ranges of 6.87–7.64 % reflects differences in fuel carbon content and combustion efficiency. HC emissions display a wider range,

covering 24–36 ppm, highlighting significant variations in unburnt hydrocarbons, particularly with the application of plastic-derived fuels. NO_x emissions show the largest range from 239 to 262 ppm, driven by differences in combustion temperature and oxygen availability. The O_2 ranges from 5.98% to 7.64% suggesting varying levels of excess air across the blends. When considering engine performance, the range for speed is 535.48–594.79 rpm, and torque is 7.94–8.23 Nm, which is narrower, reflecting the engine's operational stability regardless of the fuel type. Power output shows moderate variability of 2.13–2.22 kW, while the fuel rate ranges from 463.18 to 696.04 g/h, and the BSFC of 768.52–1507.88 g/kWh exhibits wider ranges. These variations highlight the impact of fuel type on energy conversion efficiency and fuel consumption, with biodiesel blends generally demonstrating more consistent results, while plastic-derived fuels contribute to broader ranges due to their distinct combustion properties.

The variability of the parameters demonstrates the influence of fuel type, emissions, and performance parameters. The variability, as indicated by its coefficient of variation (CV) for CO emissions, ranges from 0.38 to 0.46, showing moderate differences in incomplete combustion across blends. CO_2 production exhibits relatively low variability from 0.12 to 0.15, reflecting consistent carbon oxidation rates. HC emissions display significant CV, ranging from 0.24 to 0.41, emphasizing the impact of fuel composition on unburn HC levels. NO_x emissions variability is prominent from 0.52 to 0.56, driven by the changes in combustion temperature. O_2 shows minimal variability of CV from 0.12 to 0.15, suggesting steady excess air conditions. For performance parameters, speed and torque demonstrate low variability, with CV values of 0.10–0.12 and 0.59–0.61, respectively, showcasing the engine's operational stability across all tested fuels. Power variability is moderate (CV 0.61–0.62), reflecting differences in energy output between biodiesel and plastic-derived fuels. The fuel rate shows noticeable variability (CV 0.32–0.48), influenced by the unique combustion properties of each fuel. Finally, BSFC exhibits the highest variability (CV 0.50–0.67), underscoring the diverse fuel efficiencies and energy contents, with plastic-derived fuels contributing to greater fluctuations.

The analysis of outliers in emissions and performance parameters offers crucial insights into the variability within the dataset. CO emissions showed several outliers, indicating inconsistent combustion patterns across all tested fuels. B0 shows outliers of 90 data points, B10 (48 data points), HDPE10 (142 data points), and PP10 (90 data points). HC emissions revealed outliers only in B0, where 39 data points had values below 10 ppm. These instances reflect unusually low levels of unburnt hydrocarbons during operation. CO₂, O₂, and NO_x emissions exhibited no outliers, suggesting stable carbon oxidation and oxygen levels during combustion. As for performance parameters, speed, torque, and power showed no outliers, suggesting stable engine operation across all fuels. The fuel rate, while showing significant variability, also had no outliers, emphasizing the dynamic yet bounded nature of fuel consumption across the blends. However, BSFC presented several outliers for each fuel type, particularly at higher parameter values. These outliers indicate periods of suboptimal fuel efficiency, highlighting moments when the engine-fuel system deviated from expected performance and emission trends. B0 recorded 64 data points as outliers, B10 (179 data points), HDPE10 (179 data points), and PP10 (130 data points).

For each fuel blend evaluated, the engine was operated under two distinct engine speeds and five varying load conditions. To ensure the reliability and reproducibility of the experimental data, each operating condition was replicated three times. During each replication, which lasted approximately 30 seconds, emission parameters were recorded continuously using calibrated gas analyzers. This structured experimental design yielded a total of approximately 900 data points across all fuel types, encompassing a broad range of engine operating conditions. The number of data points after removing outliers by deleting rows is presented in Table 4.26. Extreme outliers were eliminated using the boxplot calculation method to enhance the accuracy and reliability of the trained algorithms (Fitrianto *et al.*,2022; Kigo *et al.*,2023; Nassif *et al.*,2019). The data collected from the experimental research was divided into two sets: 70% for training the models and 30% for testing. The 70% of data used for training allowed the model to learn from this dataset and adjust its parameters to minimize error. The remaining 30% of data served as untested examples to evaluate the model's ability to generalize to new, unseen data. This split is crucial for assessing the model's performance on data it hasn't encountered during training (De Simio *et*

al.,2023; Matijošius *et al.*,2024; Viana *et al.*,2023). Overall, using a 70-30 training-testing data split for the MLP model in diesel engine analysis ensures that the model is well-trained, improving its ability to make accurate predictions on new data.

The model was trained and weighted using three different training algorithms, utilizing 70% of the data, to determine which algorithm is most suitable for each biodiesel fuel blend. The training algorithms used were LM, BR, and SCG. The results for each biodiesel fuel mixture, after training with these algorithms, are presented in Tables 4.27 to 4.38, which include the R^2 , RMSE, and the corresponding equations. The best-fitting model for each blend is highlighted in bold. Figures 4.26 to 4.37 complement these tables, providing a clear visual comparison of the performance across different neuron layers.

Table 4.26 Number of final data points used

Diesel fuels	Total data points (100%)	Data points for model training (70%)	Data points for model testing (30%)
B0	728	510	218
B10	673	473	200
HDPE10	579	406	173
PP10	680	476	204

Table 4.27 Results of training by using the LM training algorithm for B0

Neurons	R ²	RMSE
1	0.9988	0.011422
2	0.99974	0.005682
3	0.99982	0.005988
4	0.99986	0.004443
5	0.99986	0.003912
6	0.9999	0.003844
7	0.99988	0.004178
8	0.99986	0.00476
9	0.99986	0.004459
10	0.99986	0.004088
11	0.99984	0.004377
12	0.99986	0.003863
13	0.9999	0.004899
14	0.9999	0.003036
15	0.99988	0.004505
16	0.99992	0.004029
17	0.99988	0.004359
18	0.9999	0.004409
19	0.9999	0.005432

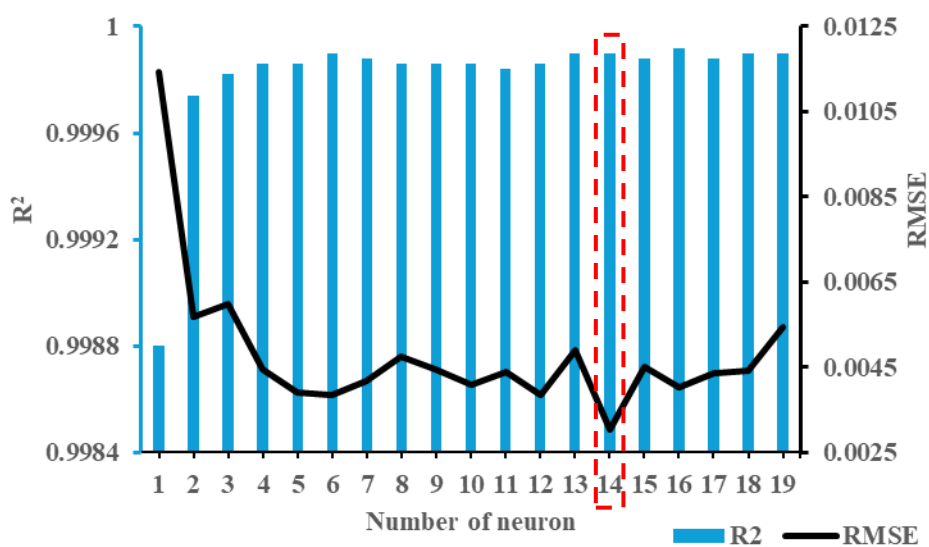


Figure 4.29 LM training algorithm for B0 displays the 14th number of neurons has the highest R² and lowest RMSE

Table 4.28 Results of training by using the BR training algorithm for B0

Neurons	R ²	RMSE
1	0.9988	0.011948
2	0.99976	0.006167
3	0.99984	0.004758
4	0.99986	0.005165
5	0.99988	0.003892
6	0.9999	0.003957
7	0.9999	0.003744
8	0.9999	0.004384
9	0.99992	0.00369
10	0.99992	0.003976
11	0.99992	0.003923
12	0.99992	0.003228
13	0.99966	0.015094
14	0.99992	0.003675
15	0.99992	0.003615
16	0.99994	0.003795
17	0.99992	0.003514
18	0.9996	0.016761
19	0.99992	0.003484

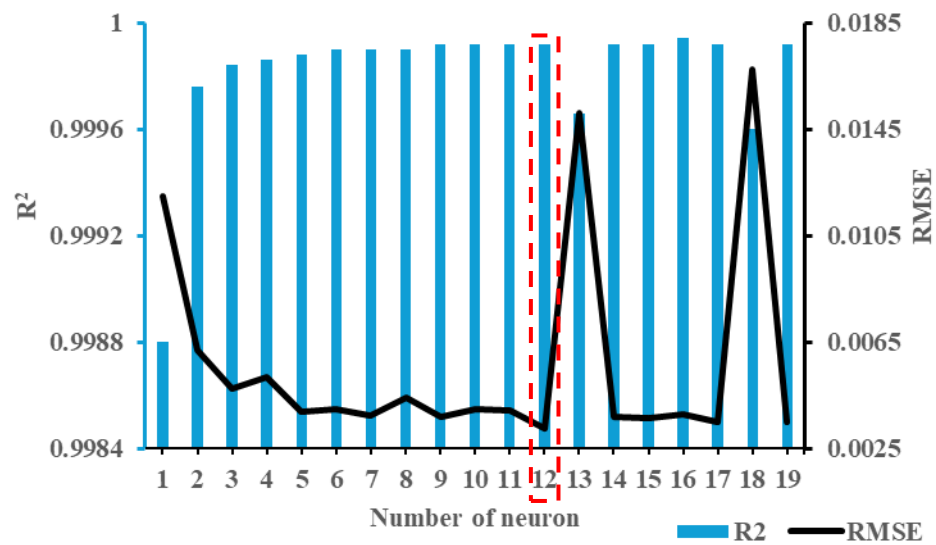


Figure 4.30 BR training algorithm for B0 displays the 12th number of neurons has the highest R² and lowest RMSE

Table 4.29 Results of training by using the SCG training algorithm for B0

Neurons	R ²	RMSE
1	0.997621	0.012118
2	0.998241	0.013109
3	0.998221	0.015122
4	0.99894	0.009124
5	0.9987	0.010233
6	0.99904	0.011856
7	0.99902	0.012482
8	0.9993	0.010574
9	0.99926	0.009117
10	0.99936	0.008922
11	0.996663	0.016759
12	0.99964	0.007521
13	0.9989	0.015317
14	0.99966	0.006412
15	0.998521	0.013592
16	0.99892	0.011221
17	0.99916	0.011796
18	0.99876	0.012182
19	0.991339	0.034641

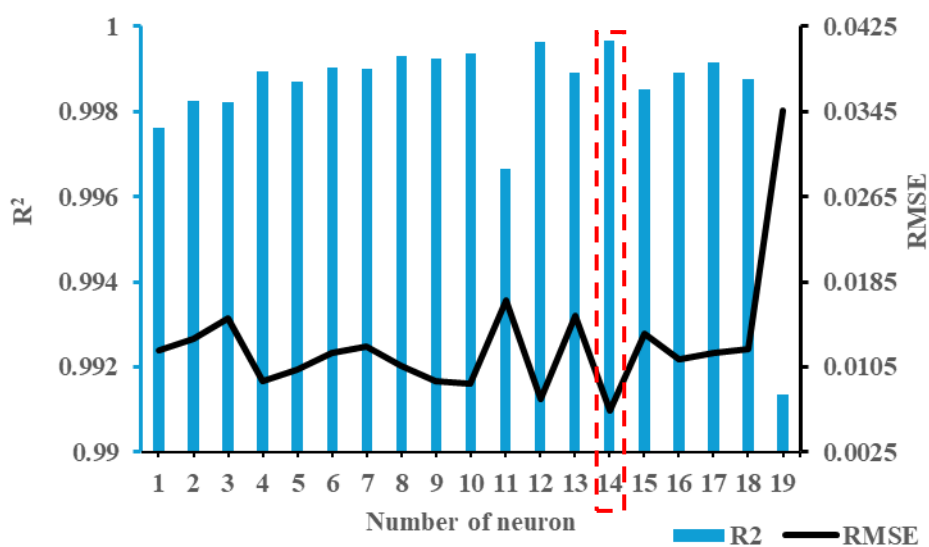


Figure 4.31 SCG training algorithm for B0 displays the 14th number of neurons has the highest R² and lowest RMSE

Table 4.30 Results of training by using the LM training algorithm for B10

Neurons	R ²	RMSE
1	0.985989	0.031035
2	0.997482	0.014074
3	0.99904	0.009864
4	0.99914	0.009433
5	0.99926	0.009377
6	0.99926	0.010133
7	0.99942	0.009395
8	0.9992	0.013629
9	0.99934	0.00693
10	0.9995	0.008191
11	0.99932	0.009153
12	0.99954	0.006946
13	0.99914	0.012741
14	0.99976	0.008563
15	0.9993	0.011414
16	0.99958	0.006765
17	0.99932	0.010452
18	0.99952	0.006358
19	0.998161	0.006981

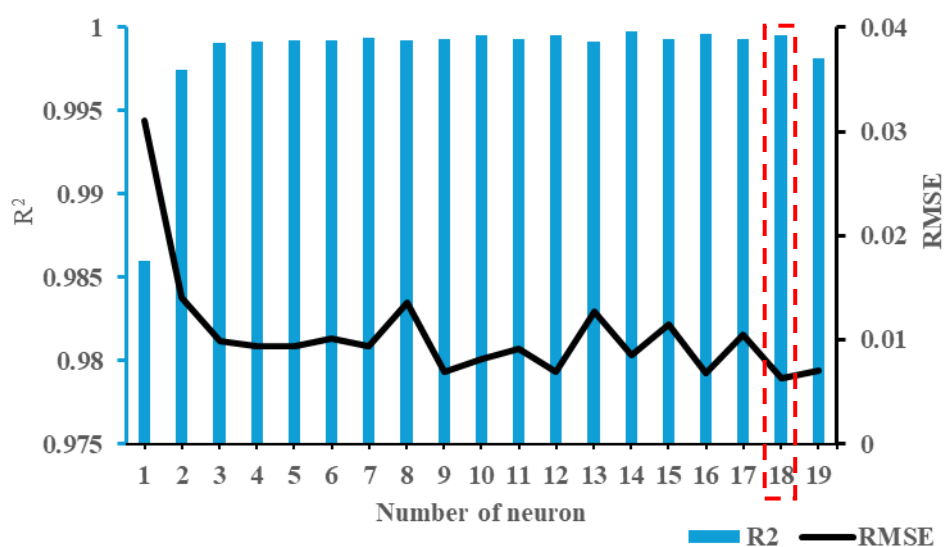


Figure 4.32 LM training algorithm for B10 displays the 18th number of neurons has the highest R² and lowest RMSE

Table 4.31 Results of training by using the BR training algorithm for B10

Neurons	R ²	RMSE
1	0.982041	0.042426
2	0.998581	0.011165
3	0.99916	0.008202
4	0.99932	0.008712
5	0.99946	0.009773
6	0.99966	0.008388
7	0.99966	0.009706
8	0.99972	0.00795
9	0.99972	0.006746
10	0.99974	0.007202
11	0.99982	0.006622
12	0.99984	0.005232
13	0.9998	0.007776
14	0.9998	0.007706
15	0.9998	0.009225
16	0.99974	0.00969
17	0.99982	0.006971
18	0.9998	0.005398
19	0.99958	0.014917

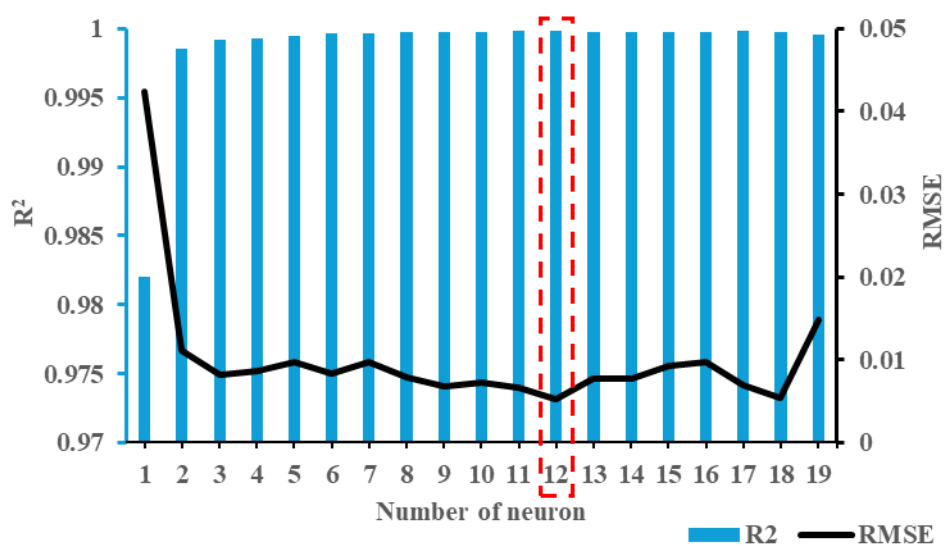


Figure 4.33 BR training algorithm for B10 displays the 12th number of neurons has the highest R² and lowest RMSE

Table 4.32 Results of training by using the SCG training algorithm for B10

Neurons	R ²	RMSE
1	0.981427	0.041231
2	0.988513	0.037417
3	0.986049	0.036056
4	0.987817	0.031623
5	0.995306	0.023475
6	0.994847	0.023179
7	0.994887	0.02529
8	0.995246	0.022552
9	0.996263	0.022891
10	0.993231	0.0254
11	0.995345	0.026364
12	0.997901	0.015784
13	0.998481	0.010383
14	0.998341	0.011881
15	0.995066	0.020699
16	0.992215	0.023287
17	0.992155	0.024789
18	0.995864	0.024217
19	0.995425	0.02289

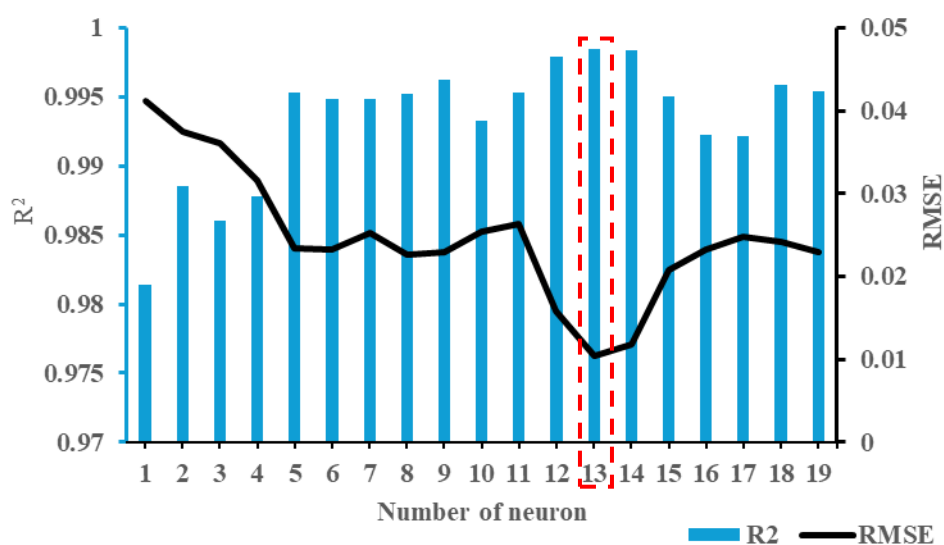


Figure 4.34 SCG training algorithm for B10 displays the 13th number of neurons has the highest R^2 and lowest RMSE

Table 4.33 Results of training by using the LM training algorithm for HDPE10

Neurons	R ²	RMSE
1	0.994149	0.021729
2	0.995026	0.029121
3	0.997701	0.025676
4	0.995884	0.009828
5	0.995784	0.027938
6	0.997102	0.014769
7	0.996383	0.020951
8	0.990602	0.033166
9	0.997202	0.009714
10	0.996982	0.021645
11	0.996343	0.018403
12	0.996283	0.013461
13	0.997062	0.009653
14	0.997961	0.007928
15	0.995385	0.027161
16	0.997522	0.008739
17	0.997881	0.011748
18	0.998521	0.012391
19	0.997901	0.012762

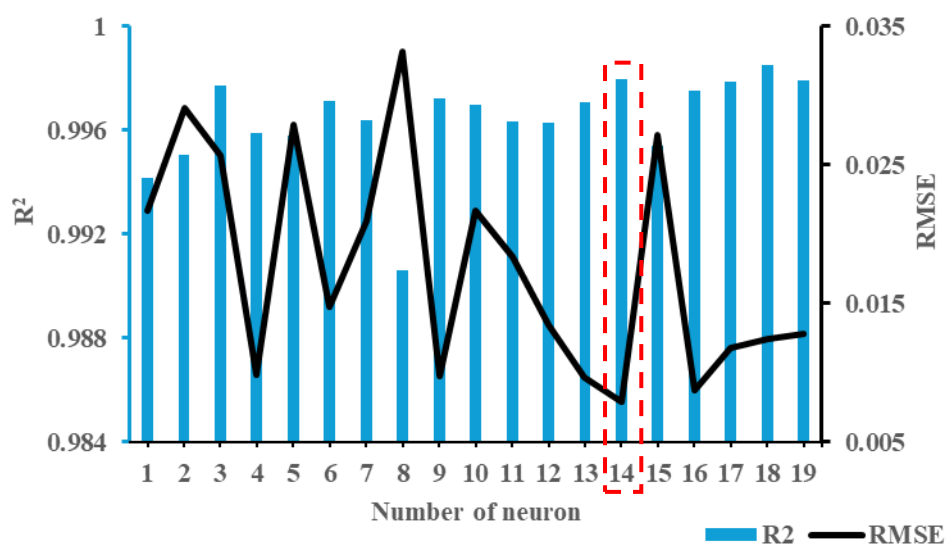


Figure 4.35 LM training algorithm for HDPE10 displays the 14th number of neurons has the highest R² and lowest RMSE

Table 4.34 Results of training by using the BR training algorithm for HDPE10

Neurons	R ²	RMSE
1	0.995944	0.018975
2	0.995725	0.020303
3	0.997522	0.023956
4	0.998101	0.008026
5	0.997961	0.010853
6	0.998341	0.009673
7	0.998481	0.008954
8	0.998461	0.007881
9	0.997082	0.030463
10	0.998561	0.025358
11	0.998481	0.019442
12	0.99874	0.024571
13	0.998361	0.027777
14	0.998321	0.017774
15	0.99896	0.00881
16	0.982577	0.095917
17	0.998321	0.010642
18	0.99888	0.012198
19	0.992693	0.05831

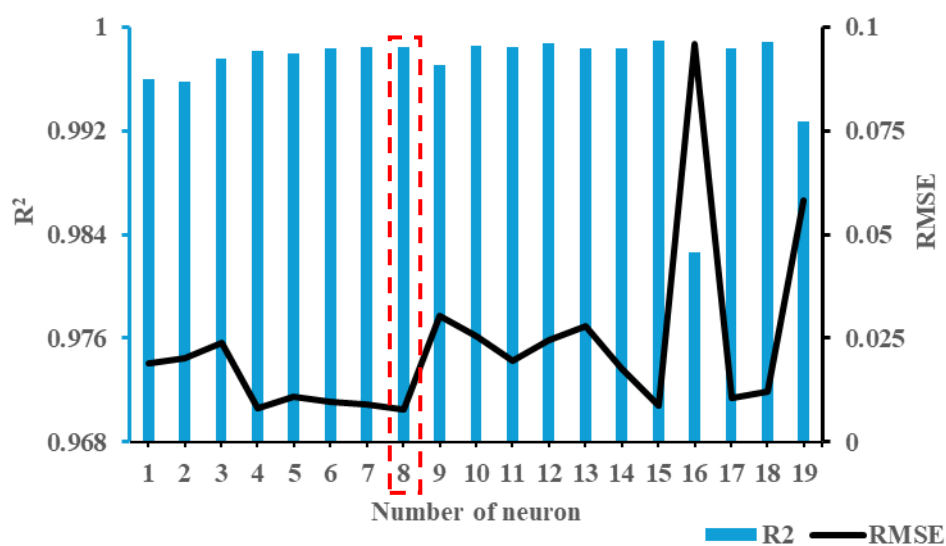


Figure 4.36 BR training algorithm for HDPE10 displays the 8th number of neurons has the highest R^2 and lowest RMSE

Table 4.35 Results of training by using the SCG training algorithm for HDPE10

Neurons	R ²	RMSE
1	0.992155	0.023142
2	0.991657	0.026048
3	0.994089	0.016761
4	0.992295	0.021033
5	0.993351	0.021554
6	0.994647	0.027711
7	0.993471	0.03042
8	0.98595	0.021384
9	0.992315	0.026695
10	0.992913	0.025432
11	0.991677	0.027703
12	0.994288	0.017446
13	0.990503	0.023062
14	0.992175	0.023533
15	0.990144	0.029885
16	0.992474	0.020134
17	0.993192	0.023291
18	0.99116	0.026511
19	0.995425	0.017812

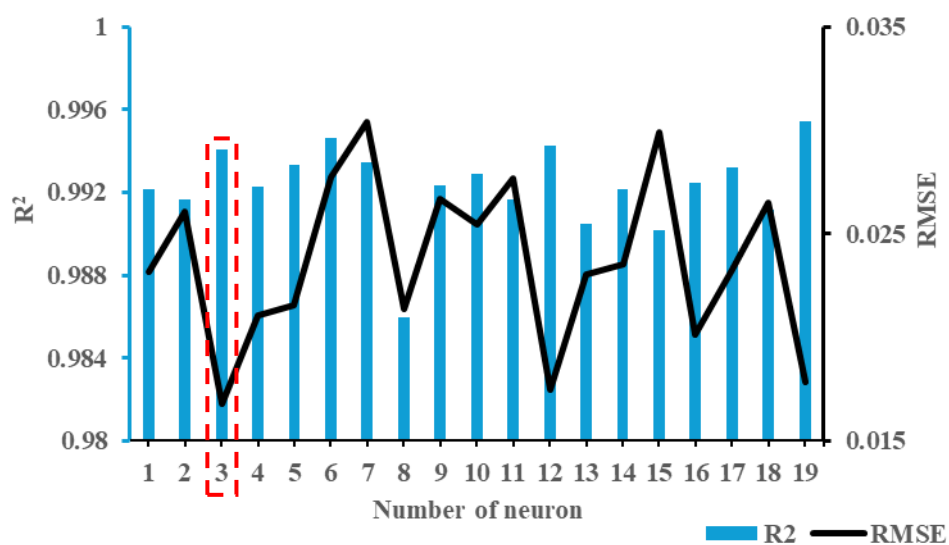


Figure 4.37 SCG training algorithm for HDPE10 displays the 3rd number of neurons has the highest R² and lowest RMSE

Table 4.36 Results of training by using the LM training algorithm for PP10

Neurons	R^2	RMSE
1	0.998201	0.012624
2	0.9991	0.009151
3	0.99934	0.007866
4	0.9993	0.008889
5	0.99922	0.008479
6	0.99924	0.006751
7	0.99934	0.013959
8	0.99962	0.007224
9	0.99934	0.007
10	0.99928	0.014747
11	0.99946	0.009146
12	0.99938	0.005772
13	0.99938	0.008888
14	0.99932	0.009324
15	0.9995	0.007981
16	0.99936	0.013363
17	0.99948	0.008091
18	0.99942	0.006339
19	0.99948	0.009568

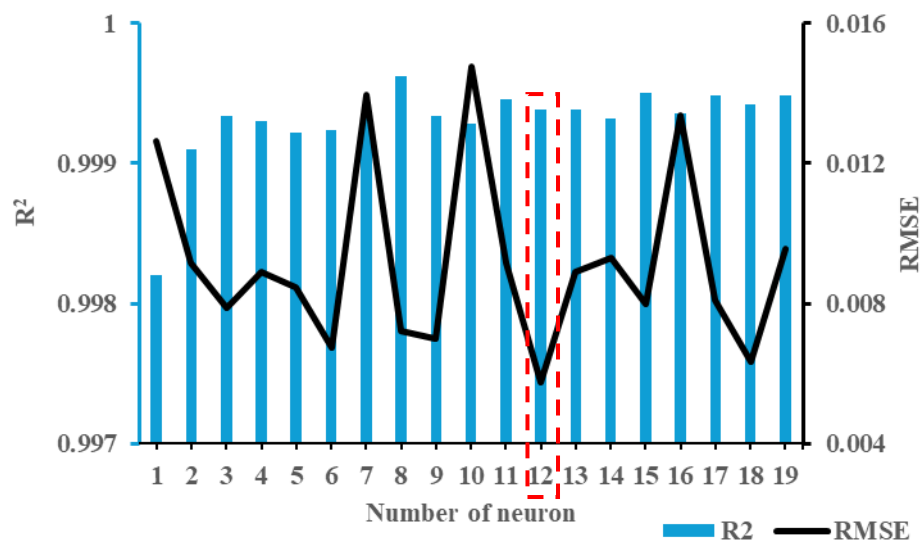


Figure 4.38 LM training algorithm for PP10 displays the 12th number of neurons has the highest R^2 and lowest RMSE

Table 4.37 Results of training by using the BR training algorithm for PP10

Neurons	R ²	RMSE
1	0.998201	0.016891
2	0.99926	0.008215
3	0.99936	0.008613
4	0.9994	0.009777
5	0.99954	0.007465
6	0.99962	0.006984
7	0.99964	0.007811
8	0.99958	0.013909
9	0.9997	0.007404
10	0.99966	0.009516
11	0.99976	0.004877
12	0.99974	0.010156
13	0.99976	0.006208
14	0.9997	0.006646
15	0.99942	0.017596
16	0.99974	0.006476
17	0.99968	0.008902
18	0.99964	0.015145
19	0.99964	0.014234

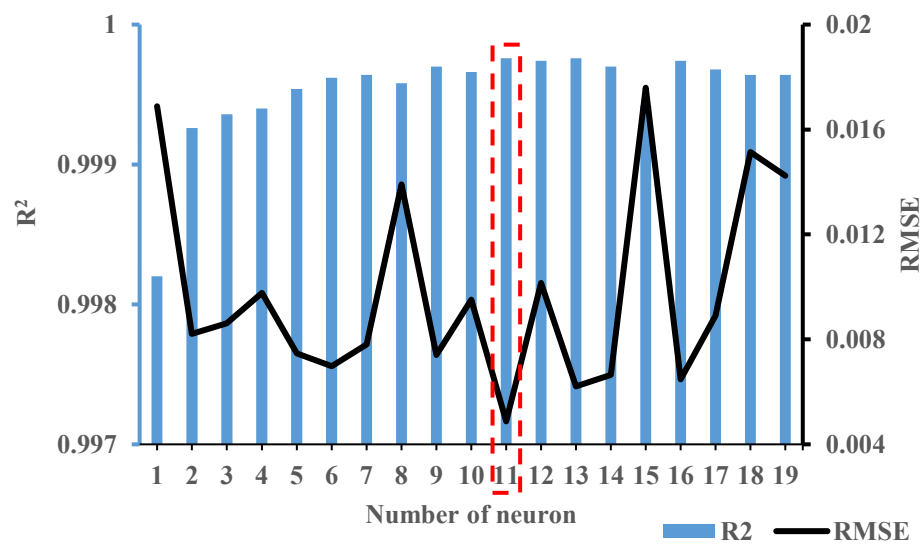


Figure 4.39 BR training algorithm for PP10 displays the 11th number of neurons has the highest R^2 and lowest RMSE

Table 4.38 Results of training by using the SCG training algorithm for PP10

Neurons	R ²	RMSE
1	0.995884	0.023182
2	0.995645	0.026495
3	0.994149	0.025004
4	0.994887	0.02671
5	0.996823	0.021503
6	0.996443	0.021646
7	0.9988	0.016156
8	0.996263	0.017273
9	0.9987	0.018497
10	0.996343	0.018004
11	0.997002	0.019987
12	0.997601	0.014319
13	0.9989	0.009729
14	0.994428	0.029758
15	0.997302	0.0143
16	0.996942	0.018655
17	0.99902	0.014879
18	0.998161	0.018347
19	0.996224	0.026045

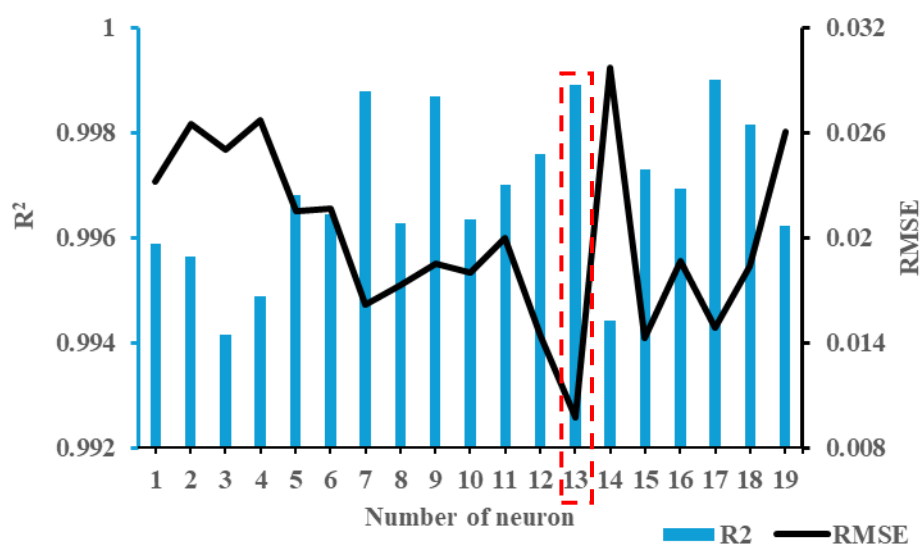


Figure 4.40 SCG training algorithm for PP10 displays the 13th number of neurons has the highest R² and lowest RMSE

Table 4.39 summarizes the analysis of the best predictive model performance of NO_x emissions across four different fuel types from B0, B10, HDPE10, and PP10 using three training algorithms of LM, BR, and SCG. The best-fitted model is marked in bold for each type of diesel fuel used. It reveals differences in accuracy and accuracy. The results provide key insights into how each algorithm performs based on R², RMSE, and the optimum number of neurons required.

Table 4.39 Summarize the results of three different training algorithms for different diesel fuels

Training algorithm	The optimum number of neurons	R ²	RMSE (g/kWh)
1). B0			
i.LM	14	0.9999	0.003036
ii.BR	12	0.99992	0.003036
iii.SCG	14	0.99966	0.006412
2). B10			
i.LM	18	0.99952	0.006358
ii.BR	12	0.99984	0.005232
iii.SCG	13	0.99848	0.010383
3). HDPE10			
i.LM	14	0.99796	0.007928
ii.BR	8	0.99846	0.007881
iii.SCG	3	0.99409	0.016761
4). PP10			
i.LM	12	0.99938	0.005772
ii.BR	11	0.99976	0.004877
iii.SCG	13	0.9989	0.009729

For B0 fuel, both LM and BR delivered near-perfect predictions, achieving R² values of 0.9999 and 0.99992 with very low RMSE values of 0.003036 g/kWh for each of the training algorithms. While SCG also performed well with an R² of 0.99966, its RMSE of 0.006412 g/kWh was slightly higher, indicating slightly reduced accuracy. The BR achieved the same high accuracy with fewer neurons of 12, compared to LM, which achieved its optimum at 14 neurons, making it the more computationally

efficient option. For B10 fuel, BR stood out again as the best-performing algorithm, achieving the highest R^2 (0.99984) and lowest RMSE (0.005232 g/kWh) with only 12 neurons. LM closely followed with an R^2 of 0.99952 and RMSE of 0.006358 g/kWh that required 18 neurons. SCG showed slightly lower accuracy with an R^2 of 0.99848, a higher RMSE of 0.010383 g/kWh requiring 13 neurons to achieve this performance.

The performance differences become more apparent with HDPE10 fuel. BR maintained its superiority, achieving an R^2 of 0.99846 and RMSE of 0.007881 g/kWh while using just 8 neurons. LM also performed well with an R^2 of 0.99796 and RMSE of 0.007928 g/kWh but required 14 neurons. SCG struggled with this more complex blend, showing a slightly lower R^2 of 0.99409, a significantly higher RMSE of 0.016761 g/kWh even though it required just 3 neurons. For PP10 fuel, BR again excelled with the highest R^2 (0.99976), lowest RMSE (0.004877 g/kWh) while using 11 neurons. LM followed closely with an R^2 of 0.99938 and RMSE of 0.005772 g/kWh requiring 12 neurons. SCG, though accurate R^2 (0.9989), showed higher RMSE values (0.009729 g/kWh) and required 13 neurons.

The best training algorithm in this study was the BR. This is due to its ability to balance accuracy, generalization, and computational efficiency as reported by Kayri (2016) and Khan and Rue (2021). BR consistently delivered the highest R^2 values across all fuel types, ranging from 0.99846 to 0.99992. These results indicate that BR provided the closest alignment between actual and predicted NO_x emission values, effectively capturing the underlying patterns in the data. Unlike LM and SCG, which can occasionally overfit or underfit depending on the dataset, BR employs an advanced regularization mechanism that enhances generalization by preventing overfitting while maintaining high predictive accuracy. (Fila *et al.*, 2024; Burden & Winkler, 2008). This feature dynamically adjusts the complexity of the model during training, preventing overfitting and ensuring strong generalization to unseen data. In terms of error reduction, BR consistently achieved the lowest RMSE across all fuel types, highlighting its precision in minimizing prediction errors. B10 fuel showed BR with an RMSE of 0.005232 g/kWh, outperforming LM (0.006358 g/kWh) and SCG (0.010383 g/kWh). For PP10, BR achieved an RMSE of 0.004877 g/kWh, further surpassing LM (0.005772 g/kWh) and SCG (0.009729 g/kWh). These lower RMSE

values confirm the ability of BR to generate more accurate predictions with fewer errors, especially when dealing with alternative fuel blends like B10 and PP10 (Zhang *et al.*, 2022).

BR demonstrated superior neuron efficiency compared to LM and SCG in most cases, making it the most computationally efficient training algorithm. For HDPE10, BR achieved high accuracy with just 8 neurons, while LM required 14 neurons to achieve slightly lower performance. For PP10, BR required only 11 neurons, compared to LM and SCG, which required 12 and 13 neurons, respectively. This reduced neuron count translates to lower computational demand and faster training times, making BR especially advantageous for larger datasets or scenarios requiring quick iterations (Froese & Hertrich, 2023; Heng *et al.*, 2022). BR can adapt to the complexity of diesel blends. The BR outperformed the SCG with high accuracy and low error. In the case of HDPE10, the R^2 for SCG dropped to 0.99409, while its RMSE increased markedly to 0.016761 g/kWh. In comparison, BR achieved an R^2 of 0.99846 and an RMSE of 0.007881 g/kWh, showing its ability to handle datasets with non-linear patterns and varying complexities. This robustness is a critical factor when working with diverse fuel blends and their complex emission characteristics. The overall performance of BR in terms of accuracy, minimal prediction errors, computational efficiency, and its capacity to handle complex datasets underscores its suitability as the most reliable training algorithm for this study (Burden & Winkler, 2008). These advantages make BR an ideal choice for predictive modelling in diesel engine research involving alternative fuel blends.

Despite the advantages of BR, LM also comes with superior characteristics. LM consistently achieved high R^2 values across all fuel types, indicating a strong correlation between predicted and actual NO_x emissions (Odufuwa *et al.*, 2025). LM achieved an R^2 of 0.9999 for B0 and 0.99938 for PP10, demonstrating its ability to deliver near-perfect predictions in most cases. LM performed well with complex fuel blends from HDPE10 and PP10, achieving competitive R^2 values of 0.99796 and 0.99936, and low RMSE of 0.007928 g/kWh and 0.005772 g/kWh, respectively, making it suitable for datasets with non-linear relationships. Although slightly outperformed by BR in some cases, LM consistently delivered reliable predictions

across all fuel types, of its versatility (Yan *et al.*, 2023). LM also demonstrated its ability to improve accuracy when allowed to use more neurons (Mustafidah *et al.*, 2019; Nawi *et al.*, 2016). LM required 14 neurons for HDPE10 and 18 neurons for B10 to achieve strong results. This suggests its potential for fine-tuning with increased computational resources. While not as precise as BR in minimizing RMSE, LM achieved reasonably low RMSE values. RMSE for B10 was 0.006358 g/kWh and 0.005772 g/kWh for PP10, highlighting its capability to deliver accurate predictions with minimal errors.

The LM training algorithm demonstrated strong performance but also exhibited several limitations. One key drawback is its higher computational demand as LM generally requires more neurons to achieve comparable or slightly lower accuracy than the BR algorithm (Bilski *et al.*, 2023; Yan *et al.*, 2021). LM needed 18 neurons compared to 12 neurons in BR for B10, and LM required 14 neurons compared to 8 neurons in BR for HDPE10. This increased neuron count results in longer training times and higher computational resource consumption, making LM less efficient, particularly for larger datasets or applications requiring rapid iterations. Another limitation is the lack of a built-in regularization mechanism, which makes it more susceptible to overfitting, especially when working with small or noisy datasets for LM (Fischer *et al.*, 2024; Troiano *et al.*, 2024). This can reduce its generalization capability when applied to unseen data. Furthermore, LM exhibited slightly lower efficiency in minimizing errors as reflected in its higher RMSE values compared to BR. The RMSE for LM was 0.006358 g/kWh, while BR achieved a lower RMSE of 0.005232 g/kWh for B10. For HDPE10, the RMSE for LM was 0.007928 g/kWh slightly higher than the RMSE for BR, which is 0.007881 g/kWh. While LM performed well with complex data, its adaptability to non-linear patterns and higher complexity was slightly inferior to BR. Lastly, the absence of dynamic regularization in LM can make it challenging to balance model complexity, further increasing its vulnerability to overfitting (Luo *et al.*, 2023). These limitations suggest that while LM remains a robust training algorithm, its computational inefficiency and reduced adaptability make it less suitable than BR for applications involving complex datasets or requiring high computational efficiency.

The SCG presents several advantages in the context of predicting NO_x emissions across different fuel types. One of its key strengths is the ability to achieve reasonable accuracy with fewer neurons, particularly for simpler datasets (Bernal & Torres-Jimenez, 2015; Sato *et al.*, 2024). SCG only required 3 neurons to attain an R^2 value of 0.99409 when using HDPE10 fuel, lower than the accuracy achieved by the BR and LM algorithms, highlighting its reduced computational demand. This feature makes SCG an appealing choice for simpler models or datasets, as it can deliver satisfactory performance with lower resource consumption. Additionally, SCG demonstrated moderate but consistent accuracy across various fuel types, achieving high R^2 values of 0.99966 for B0 and 0.9989 for PP10, indicating its ability to maintain a reasonable correlation between predicted and actual values. This balanced accuracy, combined with its reduced neuron count, results in improved computational efficiency, particularly in cases where resources are limited. Even in more complex datasets, SCG maintained reliable performance, though its R^2 and RMSE were slightly inferior to those of BR and LM.

Despite its advantages, the SCG algorithm has certain disadvantages compared to the BR algorithm. One notable limitation is its slightly lower predictive accuracy. While SCG achieved an R^2 of 0.99409 for HDPE10 fuel, BR consistently delivered higher accuracy across all fuel types, often with R^2 values closer to 1. Similarly, RMSE values from the SCG algorithm were generally higher than the BR algorithm, indicating less precise predictions. The performance of SCG tends to be less robust for complex datasets, as it can struggle to capture sophisticated relationships in the data as effectively as BR (Bernal & Torres-Jimenez, 2015). This is largely due to the ability of BR to optimize both the weights and the regularization parameters, which enhances its generalization capability and prevents overfitting. While SCG is computationally efficient, this comes at the cost of slightly reduced precision, making it less suitable for applications where absolute accuracy is critical (Sujatha *et al.*, 2022). Overall, the SCG algorithm is a more resource-efficient option, but its predictive performance and robustness lag the more sophisticated BR algorithm in complex scenarios.

The multilayer structures for function approximation are used in this study, which is based on the Kolmogorov approximation theory, serving as the basis of the

development of ANN in this study. The best architecture was found as the 30 neurons in the hidden layer after several trial-and-error methods were performed. The model was trained using the SCG algorithm, which offered efficient convergence and stable learning. Compared to the multiple linear regression (MLR) model, the ANN model demonstrated significantly superior predictive capabilities. The R^2 values for the ANN were 0.92 for NO_2 and 0.94 for NO_x emissions, indicating a strong correlation between the predicted and actual values. In contrast, the MLR model only achieved R^2 values of 0.41 and 0.44 for NO_2 and NO_x emissions, respectively (Rahimi, 2017). Domínguez-Sáez *et al.* (2018) demonstrated a comparison of CO_2 and NO_x through ANN and Symbolic Regression (SR). The ANN model achieved high predictive accuracy for both CO_2 ($R^2 = 0.93$, $\text{RMSE} = 0.0533$) and NO_x ($R^2 = 0.89$, $\text{RMSE} = 0.0453$). These results suggest that ANN effectively captured the nonlinear relationships between engine input parameters and emissions output. The low RMSE values further indicate the model's reliability in providing precise estimates with minimal deviation from actual values. On the other hand, the SR model performed comparably in predicting CO_2 ($R^2 = 0.93$, $\text{RMSE} = 0.5015$) but showed weaker performance in predicting NO_x emissions ($R^2 = 0.84$, $\text{RMSE} = 13.5415$). While SR offers the advantage of providing interpretable, analytical expressions that can be insightful for understanding underlying physical relationships, its reduced performance indicates limitations in modelling complex, nonlinear, and dynamic combustion phenomena. These results underscore the advantage of MLP in capturing the nonlinear relationships inherent in emission prediction, which traditional linear models like MLR fail to effectively represent.

Previous studies have shown the successful ness of predicting engine emissions using ANN with different training algorithms and architectures. Among them, the model developed by Kumar *et al.* (2020) using the LM algorithm with 15 neurons achieved exceptional accuracy for NO_x prediction ($R^2 = 0.99526$, $\text{RMSE} = 0.0047$), along with similarly outstanding performance across CO, CO_2 , HC, smoke, BSFC, and BTE. This comprehensive model is among the most accurate and balanced reported in the literature. Similarly, Prasada Rao *et al.* (2017), using LM with 23 neurons, attained very high accuracy for NO_x ($R^2 = 0.998$, $\text{RMSE} = 0.0316$) and consistently strong results across multiple emission and performance metrics, demonstrating the

effectiveness of moderate-sized, well-optimized networks. As reported by Subramanian *et al.* (2021), the study revealed that using the LM model with 17 neurons displayed $R^2 = 0.9912$ and $RMSE = 4.89$ for NO_x . This model also exhibited high accuracy in predicting HC, smoke, and BTE with relatively low RMSE values, showing that even smaller networks can deliver excellent results when properly trained. In contrast, Mohan *et al.* (2024) utilized a much larger network with 100 neurons, achieving $R^2 = 0.9891$ for NO_x . However, the high RMSE value of 188.28 suggests potential issues with overfitting or sensitivity to data variation, emphasizing the importance of balancing model complexity with predictive reliability.

In conclusion, the BR algorithm demonstrates superior predictive capabilities in modelling NO_x emissions from diesel engines operating with various fuel blends. BR consistently outperformed the LM and SCG by achieving the highest R^2 value, lowest RMSE, and greater computational efficiency with fewer neurons. Its built-in regularization mechanism effectively mitigates overfitting, ensuring robust generalization across diverse datasets. While LM exhibited strong predictive performance, its higher computational demand and susceptibility to overfitting without dynamic regularization posed limitations. Although SCG has efficient computational performance, it demonstrated slightly lower predictive accuracy, making it less suitable for complex datasets. These findings underscore the significance of selecting an appropriate training algorithm in ANN-based NO_x emission modelling, where BR emerges as the most reliable and efficient choice for predictive modelling in alternative diesel fuel applications.

4.5 MLP Models Testing

In this part, 30% of the experimental data points were allocated 30% of the experimental data points were allocated for testing the predictive models to ensure a robust evaluation of their performance, as shown in Table 4.40. Three key performance indicators, R^2 , RMSE, and NAE, were utilized to evaluate and select the best-fitted model for each type of diesel fuel from B0, B10, HDPE10, and PP10. The testing results revealed significant differences in accuracy, error minimization, and computational robustness among the three training algorithms: LM, BR, and SCG.

Table 4.40 Testing of the model through performance indicator

Diesel Fuels	Training algorithm	R^2	RMSE (g/kWh)	NAE
a). B0	LM	0.990847	$1.3e^{-4}$	$2.46e^{-4}$
	BR	0.990847	$8.7e^{-5}$	$1.65e^{-4}$
	SCG	0.990847	$6.1e^{-5}$	$1.15e^{-4}$
b). B10	LM	0.990025	0.00035	$1.99e^{-6}$
	BR	0.990025	$6.9e^{-5}$	$3.93e^{-7}$
	SCG	0.990025	0.0011	$6.26e^{-6}$
c). HDPE10	LM	0.988473	0.0015	$8.87e^{-6}$
	BR	0.988473	0.0003	$1.77e^{-6}$
	SCG	0.988473	0.0024	$1.42e^{-5}$
d). PP10	LM	0.99022	$9e^{-5}$	$5.29e^{-7}$
	BR	0.99022	$2.3e^{-5}$	$1.35e^{-7}$
	SCG	0.99022	0.00099	$5.82e^{-6}$

For B0 fuel, all three algorithms achieved identical R^2 values of 0.990847, indicating a strong correlation between the predicted and actual NO_x emissions. However, BR outperformed both LM and SCG in error minimization by achieving the lowest RMSE of 8.7×10^{-5} g/kWh and NAE of 1.65×10^{-4} . SCG displayed slightly higher RMSE and NAE values than BR but performed better than LM, which exhibited the highest errors for this fuel type. For B10 fuel, R^2 values were 0.990025 for all training algorithms, as BR emerged as the most effective algorithm, achieving the lowest RMSE of 6.9×10^{-5} g/kWh and an NAE of 3.93×10^{-7} . The performance is

followed by LM and SCG, with SCG displaying the weakest performance, reflected by its highest RMSE of 0.0011 g/kWh and NAE of 6.26×10^{-6} . This indicates that robustness in the BR algorithm in minimizing error for diesel blends (Dharmalingam *et al.*, 2023; Zhang & Liang, 2023). The results for HDPE10 further highlighted the superiority of BR in handling alternative fuels. BR achieved an R^2 value of 0.988473, paired with an RMSE of 0.0003 g/kWh and NAE of 1.77×10^{-6} . SCG exhibited the highest RMSE of 0.0024 g/kWh and a significantly higher NAE of 1.42×10^{-5} . While LM performed better than SCG, it did not achieve the precision of BR with an RMSE of 0.0015 g/kWh. For PP10 fuel, the R^2 values were 0.99022, identical to each other. BR once again demonstrated superior performance, achieving the lowest RMSE of 2.3×10^{-5} g/kWh and NAE of 1.35×10^{-7} . SCG displayed the weakest performance with an RMSE of 0.00099 g/kWh and NAE of 5.82×10^{-6} , while LM performed competitively but did not surpass the precision of BR.

The LM and SCG algorithms also offer advantages in terms of computational efficiency and simplicity. While BR achieves superior error minimization, it involves higher computational overhead due to its complex optimization process. In terms of ML training, LM and SCG require less computational time and resources, making them more suitable for scenarios with limited resources or when faster training is needed (Ramana *et al.*, 2024; Roy *et al.*, 2021a). Both LM and SCG demonstrated moderate accuracy across fuel types, achieving identical R^2 values with BR for B0 and PP10 fuels, indicating their capability to provide acceptable performance when error minimization is not the primary focus. These algorithms are easier to implement as they do not require extensive fine-tuning of regularization parameters like BR (Mishra *et al.*, 2016; Prabhu *et al.*, 2021). SCG occasionally outperformed LM in error metrics such as RMSE and NAE for B0 fuel, while LM performed better than SCG for HDPE10 fuel, showing that each algorithm has strengths depending on the dataset (Roy *et al.*, 2021b). The computational efficiency and simplicity of LM and SCG make them practical alternatives to BR, particularly in applications where fast training or resource constraints are considerations.

While computationally efficient, the LM and SCG algorithms exhibit several disadvantages compared to the BR algorithm, particularly in terms of predictive

accuracy and error minimization. BR consistently outperformed both LM and SCG across all fuel types by achieving the lowest RMSE and NAE (Bataineh & Kaur, 2018). BR achieved an RMSE of 6.9×10^{-5} g/kWh and an NAE of 3.93×10^{-7} , whereas SCG and LM trailed behind, with SCG showing the highest RMSE of 0.0011 g/kWh for B10. Similarly, BR demonstrated high precision with an RMSE of 0.0003 g/kWh and NAE of 1.77×10^{-6} , while LM and SCG recorded higher errors, with SCG showing the lowest RMSE of 0.0024 g/kWh for HDPE10 fuel. These results highlight that LM and SCG lack the robustness of BR in handling complex datasets and minimizing prediction errors, particularly for alternative fuels like HDPE10 and PP10 (Bagherzadeh *et al.*, 2025; Jakšić *et al.*, 2023). Their performance in capturing complex relationships within the data is comparatively weaker due to the absence of an advanced regularization mechanism that enhances generalization and prevents overfitting through the BR algorithm. Consequently, while LM and SCG offer computational advantages, their reduced accuracy and weaker error minimization make them less suitable for applications where precise predictions and low errors are critical (Bataineh & Kaur, 2018; Uwimana *et al.*, 2025). Overall, BR consistently outperformed LM and SCG in terms of accuracy, error minimization, and robustness across all fuel types. Its ability to achieve the lowest RMSE and NAE values highlights its effectiveness in capturing complex and non-linear relationships within the datasets, particularly for alternative fuels like HDPE10 and PP10. This makes BR the most favourable training algorithm for the predictive modelling of NO_x emissions in diesel engine studies. In contrast, SCG has relatively higher error metrics, suggesting it may be less suitable for datasets with complex patterns, while LM did not match BR's precision.

Table 4.41: Comparison of training and testing performance metrics for MLP models using different algorithms and fuel types using R^2 drop percentage and overfitting assessment

Fuel Type	Algorithm	Training R^2	Testing R^2	R^2 Drop (%)	Overfitting Risk
B0	LM	0.9999	0.9908	0.91%	Low
	BR	0.99992	0.9908	0.91%	Low
	SCG	0.99966	0.9908	0.88%	Low
B10	LM	0.99952	0.9900	0.95%	Low
	BR	0.99984	0.9900	0.98%	Low
	SCG	0.99848	0.9900	0.85%	Low–Moderate
HDPE10	LM	0.99796	0.9885	0.95%	Low
	BR	0.99846	0.9885	1%	Low
	SCG	0.99409	0.9885	0.56%	Low–Moderate
PP10	LM	0.99938	0.9902	0.92%	Low
	BR	0.99976	0.9902	0.95%	Low
	SCG	0.9989	0.9902	0.87%	Low

Table 4.41 summarizes the training and testing performance of the MLP models using three training algorithms of LM, BR, and SCG across four different fuel types. The comparison includes key performance indicators such as R^2 , RMSE, and the percentage drop in R^2 between the training and testing phases, which is used to assess the degree of overfitting. Across all fuel types and algorithms, the models demonstrate strong performance during training, with R^2 values exceeding 0.99 in most cases. However, high training R^2 alone is insufficient to confirm model generalization. Therefore, the R^2 drop percentage was calculated to evaluate how well the model maintains its predictive performance on unseen data. A smaller R^2 drop typically indicates better generalization and a lower risk of overfitting. For the B0 and B10 fuel types, the R^2 drop remains consistently below 1% across all algorithms, suggesting minimal overfitting and stable generalization. SCG yields the lowest R^2 drop for both B0 (0.88%) and B10 (0.85%), although this comes at the expense of slightly higher RMSE values compared to LM and BR.

For HDPE10, BR maintains higher performance between accuracy and generalization, with a training R^2 of 0.99846, a testing R^2 of 0.9885, and the smallest testing RMSE (0.0003 g/kWh) among the three algorithms. Although SCG produces the lowest R^2 drop (0.56%) for this fuel, its higher RMSE in both training and testing indicates a comparatively increased, but slightly greater risk of overfitting. In the case of PP10, all algorithms exhibit stable performance with R^2 drops well below 1%. The BR algorithm again shows high performance with the highest training R^2 (0.99976), the lowest testing RMSE (2.3×10^{-5} g/kWh), and a moderate R^2 drop (0.95%). This demonstrates its robustness and strong predictive reliability. In summary, the BR algorithm consistently provides the most reliable performance across all fuel types, exhibiting low R^2 drop percentages and minimal RMSE values, which collectively indicate excellent model generalization with a low risk of overfitting. While demonstrating competitive R^2 values, the SCG algorithm occasionally shows higher RMSEs, particularly for HDPE10, suggesting a slightly elevated overfitting risk in those cases. The LM algorithm performs adequately but generally does not outperform BR in either accuracy or generalization.

These findings affirm the suitability of the MLP modelling approach for predicting NO_x emissions across a diverse range of fuel blends and engine conditions, with BR emerging as the most robust training method for ensuring both model accuracy and generalization.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This research listed 4 objectives. The first stated objective is to characterize the fuel properties of plastic-derived diesel fuels compared to the conventional B0. This objective is achieved by assessing through various laboratory tests such as FTIR, calorific value, kinematic viscosity, density, GC-FID, and CHNS elemental analysis. FTIR analysis shows that C-H stretching vibrations, including CH₂, CH₃, and CH groups, appear between 2850 and 3000 cm⁻¹. Higher transmittance values indicate a greater presence of alkane groups in all diesel blends. These peaks also reflect the concentration of hydrocarbon chains in the fuel. The bending vibrations of C-H bonds from alkane groups, specifically CH₂ and CH₃, occur between 1350 and 1480 cm⁻¹. Peaks in the 1735 to 1750 cm⁻¹ range represent the carbonyl (C=O) stretching vibrations found in esters, which indicate the presence of biodiesel or ester additives. C-O stretching vibrations appear between 1000 and 1300 cm⁻¹, corresponding to ester structures. Higher transmittance in this range suggests a higher concentration of ester groups, which helps assess the biodiesel or ester additive content in the blends. Different trends were observed in the calorific values, with B0 recording the highest at 45.652 MJ/kg, followed by PP10 (45.575 MJ/kg), B10 (45.012 MJ/kg), and HDPE10 (44.636 MJ/kg). B0 has the highest calorific value, which contains more energy per unit mass, leading to greater energy output during the combustion process. This contributes to improved engine efficiency and overall performance.

Plastic-derived diesel fuels had lower kinematic viscosity at 40°C, with HDPE10 at 3.2557 mm²/s and PP10 at 3.0634 mm²/s, while B10 had the highest at 3.7067 mm²/s. Lower viscosity improves atomization and air mixing, enhancing combustion. Density at 15°C followed a similar trend, with HDPE10 (810.38 kg/m³) and PP10 (809.4 kg/m³) being lower than B0 (814.16 kg/m³) and B10 (846.9 kg/m³). Lower-density fuels improve combustion and reduce emissions. HDPE10 and PP10 have fuel properties comparable to B0 and B10, making them suitable for diesel engines. GC-FID analysis showed higher concentrations of Hentriacontane (C₃₁H₆₄), Heptacosane (C₂₇H₅₆), and Heptadecane (C₁₇H₃₆). Medium-chain hydrocarbons like Nonacosane (C₂₉H₆₀) were also widespread, while longer chains appeared in lower concentrations. CHNS analysis revealed that B10 had the highest C (81.37%) and H (12.657%), improving energy density but slightly increasing NO_x emissions due to its 1.65% nitrogen content. HDPE10 and PP10 had lower C and H but higher oxygen (18.427% and 24.123%), promoting combustion but raising in-cylinder temperatures, potentially increasing NO_x. All blends had negligible sulfur, meeting low-sulphur diesel standards.

The second stated objective is to investigate the trend of engine performance and emissions by using the different diesel blends. Engine performance is assessed through BP, BSFC, and BTE. B0 delivers the highest BP due to its superior calorific value, while alternative fuels show slight reductions: B10 (0.27–5.4%), HDPE10 (0.26–6.97%), and PP10 (0.37–5.73%). BSFC decreases with increasing load. At low torque, all blends show higher BSFC due to incomplete combustion. At medium and high torque, HDPE10 and PP10 reduce fuel consumption by up to 25.87% and 25.09% due to better atomization. B10 shows increased BSFC at high speeds due to higher viscosity, while PP10 performs better. BTE analysis shows efficiency gains, with PP10 improving by up to 118.7% at low torque. Higher torque further enhances BTE, compensating for lower calorific values. PP10 consistently outperforms HDPE10 due to lower viscosity and superior atomization. Optimized fuel properties enhance efficiency across varying conditions.

CO emissions vary with engine speed and load. B10 shows higher CO at low loads due to incomplete combustion, while HDPE10 reduces emissions at high loads

through better oxidation. PP10 performs best, with lower viscosity improving atomization and reducing CO at medium and high loads. At 2000 rpm, B10 and HDPE10 increase CO emissions at higher loads, while PP10 reduces them. At 2500 rpm, CO emissions rise for B10 and PP10, while HDPE10 remains stable, improving at 10 Nm due to its higher calorific value. B10 produces the highest CO₂ emissions due to its oxygen content, which enhances oxidation. HDPE10 and PP10 show lower CO₂, especially at high loads. At 2000 rpm, B10 emits the most CO₂, while HDPE10 and PP10 reduce emissions. At 2500 rpm, B10 and PP10 show higher CO₂ at medium and high loads due to improved oxidation, while HDPE10 remains stable. B10 reduces HC emissions due to better oxidation. HDPE10 and PP10, with higher viscosity and long-chain hydrocarbons, show increased emissions, especially at low loads. PP10 outperforms HDPE10 due to better atomization. At 2500 rpm, B10 achieves the lowest HC emissions, while HDPE10 records the highest due to incomplete combustion. B10 is the most effective at reducing NO_x due to its oxygen content. HDPE10 and PP10 also lower NO_x, but are less effective at high loads. At 2000 rpm, B10 reduces NO_x the most, while at 2500 rpm, PP10 performs best at low loads, and HDPE10 excels at medium and high loads. B10 shows the lowest O₂ emissions, confirming its efficient combustion. HDPE10 and PP10 fluctuate, with PP10 sometimes increasing O₂, indicating incomplete combustion. O₂ trends correlate with CO, CO₂, HC, and NO_x emissions, with lower O₂ suggesting better combustion efficiency.

Developing non-linear models for predicting NO_x emissions is listed as the third objective. The BR algorithm emerged as the most effective training method for predicting NO_x emissions from diesel engines using various fuel blends. BR consistently achieved the highest accuracy, where R² is up to 0.99992, the lowest RMSE down to 0.003036 g/kWh, and greater computational efficiency with fewer neurons. Its built-in regularization minimized overfitting, ensuring strong generalization. While the LM algorithm delivered competitive accuracy, it required more neurons and was more prone to overfitting. The SCG algorithm was computationally efficient but exhibited slightly lower predictive accuracy. BR proved to be the most reliable and efficient choice for ANN-based NO_x emission modelling in alternative diesel fuel applications. The last objective is to establish the best-fitted model for NO_x emissions prediction through performance indicators. BR consistently

achieved the highest accuracy with the lowest RMSE by $8.7e^{-5}$ g/kWh and NAE by $3.93e^{-7}$ across all fuel types, making it the most reliable for complex datasets, especially using alternative fuels like HDPE10 and PP10. While LM and SCG offered faster computation, they had higher errors, making them less suitable for precise predictions. The comparative analysis of MLP model performance across various fuel types and training algorithms demonstrates that all models achieved high accuracy, with training R^2 values generally exceeding 0.99. Among the algorithms, BR consistently exhibited superior generalization capability, characterized by minimal R^2 drop percentages and the lowest RMSE values in both the training and testing phases. While the SCG algorithm occasionally achieved the smallest R^2 drop, its higher RMSE values suggest a moderately increased risk of overfitting. The LM algorithm performed adequately but did not outperform BR in any key metric. In conclusion, BR proved to be the most reliable and robust algorithm for predicting NO_x emissions, ensuring strong model generalization across diverse fuel blends and engine operating conditions.

5.2 Recommendation

Based on the findings, this research proves the success of manufacturing green and renewable energy from plastic waste into plastic-derived diesel fuels. It is useful information to expand the production of plastic-derived diesel fuels from another type of plastic waste and its mixture in conjunction with the worldwide problems related to plastic waste. The addition of plastic-derived diesel fuels to the conventional and daily use of diesel fuel is significantly beneficial, such as reducing the amount of plastic waste and the microplastic formation, establishing new green energy, and lessening air pollution.

Several suggestions may be made for future research to expand on the body of knowledge and address possible topics for additional research. First, examine the impact of varying the ratio of HDPE, PP, and other plastic types as additives on fuel characteristics, engine performance, and emissions. Optimizing the diesel blend formulation could improve engine efficiency and reduce pollutants. The effort should

include employing combustion analysis, such as in-cylinder pressure measurement and heat release analysis. It helps to gain a deeper understanding of the combustion characteristics of the diesel blends.

Future research in terms of the inclusion of PM emissions regarding the size is also beneficial in forecasting particulates, as it is more prone to affect humans and the environment when the pollutants have been highlighted as criteria pollutants in National Ambient Air Quality Standards (NAAQS) effectively implemented in 2020. Finally, to ascertain the feasibility and competitiveness of biodiesel blends with HDPE and PP additives in the market, an economic study must be performed to assess how cost-effective it is to produce and use these blends commercially. This study provides a comprehensive assessment of production costs, encompassing raw material procurement, processing, distribution, and market pricing. It also examines the potential cost advantages of using these blends as alternatives to conventional diesel. Understanding their economic feasibility is essential for informed decision-making regarding large-scale adoption and investment in expanded production for broader market integration.

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APPENDICES

Appendix 1 Certificate of B0

PETRONAS DIESEL EURO 5 (B0)

PROPERTIES	Unit	GUARANTEED LIMIT		TEST METHOD
		MINIMUM	MAXIMUM	
Total Sulfur	mg/kg	-	10.0	ASTM D5453 / D2622 / D4294 / D7039 / IP 336
Cetane Index ^a	-	49	-	ASTM D4737 / D976
or Cetane Number ^b	-	49	-	ASTM D6890 / D613 / IP 498
Density at 15°C	kg/L	-	0.845	ASTM D4052 / D1298
Physical Distillation at 95% Recovered Volume	°C	-	360	ASTM D86
or Simulated Distillation at 95% Recovered Mass	°C	-	386	ASTM D2887
Polycyclic Aromatic Hydrocarbons	% mass	-	8.0	EN 12916 / ASTM D6591
Acid Number	mgKOH/g	-	0.25	ASTM D664 / D974
Ash	% wt.	-	0.01	ASTM D482 / IP 4
Carbon Residue (on 10% bottoms)	% wt.	-	0.20	ASTM D4530 / D189 / IP 13
Cloud Point	°C	-	19.0	ASTM D5772 / D2500 / D5771 / D5773 / IP 219
Copper Corrosion (3 hours at 100°C)	-	-	1	ASTM D130 / IP 154
Color	-	-	2.0	ASTM D1500 / D6045
Electrical Conductivity	pS/m	50	-	ASTM D2624
Flash Point	°C	60	-	ASTM D93 / IP 34
Kinematic Viscosity at 40°C	mm ² /s	1.5	5.8	ASTM D445 / D7042 / IP 71
Lubricity	µm	-	460	ASMT D6079 / IP 450
Sediment by Extraction	% wt.	-	0.01	ASTM D473
Water by Distillation	% vol.	-	0.05	ASTM D95
Palm Methyl Ester	% vol.	-	0.0	ASTM D7371
APPLICATION	PRECAUTION			SPECIFICATION
Mainly use in automotive diesel engine for retail and commercial sector e.g. passenger car, light duty trucks, heavy duty trucks, prime movers and etc.	▪ Flammable liquid and vapor ▪ May be fatal if swallowed and enters airways ▪ Causes skin irritation ▪ Harmful if inhaled ▪ Suspected of causing cancer ▪ May cause damage to organs (thymus, liver, bone marrow) through prolonged or repeated exposure ▪ Toxic to aquatic life with long lasting effects			This diesel meets the following specification: ▪ SIRIM MS 123-3:2016 This diesel may contain Palm Methyl Ester (PME) complying with SIRIM MS 2008:2014 and EN 14214 Intentional additions of metallic additives shall not be allowed
^a Cetane Index is not applicable for biodiesel blend				
^b Derived Cetane Number				

Appendix 2

Certificate of B10

PETRONAS DIESEL EURO 5 (B10-B20)

PROPERTIES	Unit	GUARANTEED LIMIT		TEST METHOD
		MINIMUM	MAXIMUM	
Color (ASTM)	-	-	2.0	ASTM D1500 / D6045
Ash	%wt.	-	0.01	ASTM D482 / IP4
Cloud Point	°C	-	19.0	D5772 / D2500 / D5771 / D5773 / IP219
Flash Point	°C	60	-	ASTM D93-A / IP34
Kinematic Viscosity at 40°C	mm ² /s	1.5	5.8	ASTM D445 / D7042 / IP71
Copper Corrosion (3h at 50°C)	-	-	1	ASTM D130 / IP154
Water by Distillation	%vol.	-	0.05	ASTM D95 / D6304
Sediment by Extraction	%wt.	-	0.01	ASTM D473
Carbon Residue on 10% bottoms	%wt.	-	0.20	ASTM D189 / D4530 / IP13
Density at 15°C	kg/L	-	0.856	ASTM D1298 / D4052
Acid Number	mgKOH/g	-	0.30	ASTM D664 / D974
Electrical Conductivity	pS/m	50	-	ASTM D2624
Cetane Number	-	49	-	ASTM D613 / D6890 / IP498 / D7668
Physical Distillation at 95% Recovered Volume or Simulated Distillation at 95% Recovered Mass	°C	-	360	ASTM D86
	°C	-	386	D2887
Total Sulfur	mg/kg	-	10	ASTM D4294 / D2622 / D5453 / D7039 / D5950 / IP336
Lubricity	µm	-	460	ASTM D6079 / IP450
Polycyclic Aromatic Hydrocarbons	%wt.	-	8.0	EN 12916 / ASTM D6591
Palm Methyl Ester (PME)	%vol.	7.1	20.0	ASTM D7371
APPLICATION	PRECAUTION			SPECIFICATION
Mainly use in diesel engine for retail and commercial sector e.g., passenger car, light duty trucks, heavy duty trucks, prime movers and etc.	▪ Flammable liquid and vapor ▪ May be fatal if swallowed and enters airways ▪ Causes skin irritation ▪ Harmful if inhaled ▪ Suspected of causing cancer ▪ May cause damage to organs (thymus, liver, bone marrow) through prolonged or repeated exposure ▪ Toxic to aquatic life with long lasting effects			This diesel meets the following specification: ▪ MS 123-5:2020 Intentional additions of metallic additives shall not be allowed. PME shall meet the requirements of MS 2008.

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