Response Surface Methodology and Artificial Neural Network Methods for Optimization of Performance and Emission Characteristics of Diesel Engine Using Diesel-n-butanol Blend

Bekuma Abera Mosisa

A Thesis Submitted to

The Department of Mechanical Engineering

College of Mechanical, Chemical, and Materials Engineering

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Automotive Engineering

School of Postgraduate Studies

Adama Science and Technology University

February 2026

Adama, Ethiopia

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CANDIDATE DECLARATION

I declare that this thesis entitled "**Response Surface Methodology and Artificial Neural Network Methods for Optimization of Performance and Emission Characteristics of Diesel Engine Using Diesel-n-butanol Blend"** is my own work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

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RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "**Response Surface Methodology and Artificial Neural Network Methods for Optimization of Performance and Emission Characteristics of Diesel Engine Using Diesel-n-butanol Blend**" prepared under my guidance by **Bekuma Abera** submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Automotive Engineering. Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

___________________	___________________	______________
Major Advisor	Signature	Date

APPROVAL PAGE FOR MSc. THESIS

I/we, the advisors of the thesis entitled "**Response Surface Methodology and Artificial Neural Network Methods for Optimization of Performance and Emission Characteristics of Diesel Engine Using Diesel-n-butanol Blend**" by **Bekuma Abera**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor/Supervisor	Signature	Date

We, the undersigned, members of the board of examiners of the thesis by Bekuma Abera have read and evaluated the thesis entitled "Response Surface Methodology and Artificial Neural Network Methods for Optimization of Performance and Emission Characteristics of Diesel Engine Using Diesel-n-butanol Blend" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Automotive Engineering.

Chairperson	Signature	Date
Internal Examiner	Signature	Date
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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head	Signature	Date
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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURES

AASTU	Addis Ababa Science and Technology University
ABE	Acetone-butanol-ethanol
Adj-R^2	Adjusted coefficient of determination
B0	Pure diesel
B10	10% of n-butanol and 90 % of diesel
B20	20% of n-butanol and 80 % of diesel
B30	30% of n-butanol and 70 % of diesel
BBD	Box-Behnken design
BMEP	Brake mean effective pressure
BP	Brake power
BSFC	Brake-specific fuel consumption
BT	Brake torque
BTE	Brake thermal efficiency
CCD	Central composite design
CDC	Conventional diesel combustion
CDE	Conventional diesel engine
CFD	Computational fluid dynamics
CI	Compression engine
CN	Cetane number
CNG	Compressed natural gas
CO	Carbon monoxide
CP	Cylinder pressure
CRDI	Common rail direct injection

CR	Compression ratio
CO_2	Carbon dioxide
CT	Cylinder temperature
CV	Calorific value
DAS	Data acquisition system
DI	Direct injection
DOE	Design of experiment
EGA	Exhaust gas analyzer
EGR	Exhaust gas recirculation
EGT	Exhaust gas temperature
FFD	Full factorial design
HC	Hydrocarbon
HRR	Heat release rate
ICE	Internal combustion engine
ID	Ignition delay
IMEP	Indicated mean effective pressure
IT	Injection timing
ITE	Indicated thermal efficiency
LHV	Latent heat of vaporization
LPG	Liquefied petroleum gas
LTC	Low temperature combustion
MFC	Mass fuel consumption
MPRR	Maximum pressure rise rate
MSE	Mean square error

NOx	Nitrogen oxides
PODE	Polyoxymethylene dimethyl ether
PM	Particulate matter
PODE	Polyoxymethylene dimethyl ether
R^2	Coefficient of determination
RMSE	Root mean square error
rpm	Revolution per minute
RSM	Response surface methodology
SI	Spark ignition
SOI	Start of injection
SSE	Sum square of the errors
TDC	Top dead center
UHC	Unburnt hydrocarbons
VCR	Variable compression ratio

ABSTRACT

Due to the growing demand for more sustainable and environmentally friendly energy sources, extensive research has been done to reduce emissions and boost the efficiency of CI engines. These engines are known to contribute to two main environmental contaminants: PM and NOx. Among the other alternative fuels that have been researched, n-butanol has shown great potential due to its high oxygen content, considerable latent heat of vaporization, and rapid flame propagation rate, all of which contribute to more efficient and clean combustion. This study combines ANN and RSM techniques to optimize the emissions and performance characteristics of a CI engine running on diesel-n-butanol blends. Pure diesel (B0) and blends including 10%, 20%, and 30% n-butanol (B10, B20, and B30) were used in the experimental testing. An ultrasonicator was used to achieve homogeneous fuel preparation. B10 demonstrated the most balanced performance of all the fuels tested, greatly lowering CO_2 *and NOx while keeping braking torque (BT) and brake power (BP) on level with regular diesel. Higher blends produced incomplete combustion, which increased emissions of CO and HC, but they also* CO_2 *and NOx. By maximizing BT and BP and minimizing* $BSFC$ *and emissions, RSM optimization-based central composite design was employed to determine the ideal operating parameters. BT of 4.18 Nm, BP of 1.52 kW, BSFC of 0.379* kg/kWh, CO_2 *of 3.4277*$\%vol$, *CO of 0.0318* $\%vol$, *NOx of 148* pmm , *and HC of 26* pmm *were the results of the ideal conditions, which were reached at 49.79% engine load and 10% n-butanol ratio. As demonstrated by better* R^2 *and lower error measures (MSE and RMSE), comparative research showed that ANN offered more prediction accuracy than RSM. The nonlinear interactions between engine inputs and responses were successfully represented using ANN. In general, the study showed that using statistical modeling coupled with n-butanol can improve the performance of CI engines and lower emissions. This integrated strategy contributes to the development of sustainable alternative fuels and environmental conservation by providing an approach toward cleaner and more efficient engines.*

***Keywords*:** Engine, n-butanol, Performance, RSM, ANN, Emission

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

Nonrenewable energy is getting special attention to transportation, agricultural, and industrial sectors. Fossil fuels contributes over 80% of worldwide energy. 30% of global energy consumed by the transportation sector and with an astounding 80% of that energy being used for road transportation. Over 60% of the world's oil needs are currently met by this sector, which is predicted to grow at the fastest rate in the coming years (Tvaronavičienė et al., 2020). There are natural sources of energy which are both affordable and environmentally sustainable when compared to other sources of energy. Due to issues with energy security such as the depletion of petroleum resources, and other socioeconomic factors, researchers are looking forward to find natural sources of energy (Kumar & Paul, 2023). Majority of engines found in automobiles, ships, trains, and various industrial equipment have diesel. Diesel engines are known for their high thermal efficiency and minimal CO_2 emissions. However, they contribute significantly to the discharge of harmful pollutants like PM, CO, NOx, and UHC. Emissions of gas from petroleum-diesel pose a threat to both environmental integrity and public health. Even with these drawbacks, diesel engines are still widely used in many applications due to their high thermal efficiency and low cost. Majority of transportation sectors are mainly well-linked to Diesel engines due to their higher power output and fuel efficiency(Siva Prasad et al., 2024).

Conventional diesel combustion (CDC) working principle is based on compression ignition which uses high reactivity fuels like diesel that are ignited at high temperatures by regulated mixing. NOx and PM are frequently released as exhaust as result of this ignition(Azizzadeh Hajlari et al., 2019). To react to new emission regulations and the growing demand for fossil fuels, Combustion processes improve by four basic strategies such as altering engine designs, using alternative fuels, installing exhaust after-treatment systems, and introducing advanced combustion concepts to lower the exhaust emissions associated with conventional diesel combustion while still adhering to emission regulations (Noh & No, 2017). To minimize environmental pollution successful strategy is required. The use of alternative renewable fuels is recognized as this strategy. This effective approach, it is believed that using sustainable and alternative fuels, such as natural gas, alcohol, biodiesel, and dimethyl ester, can greatly lower NOx, PM, and greenhouse gas emissions from diesel engines (Liu et al., 2022). Many studies on the impact of n-butanol on CI engine performance have been conducted in recent years.

Mixture of Bio-butanol and gasoline perform dual function as a fuel and an oxygen booster in SI engines. The combination of diesel and n-butanol can also be used in diesel engines since their distinct properties, particularly the Cetane Number, are found to be comparable to those of pure diesel (Gwalwanshi et al., 2022). Diesel engine's performance needs to be improved while its harmful emission has to be reduced due to international restriction on emission of harmful gases. Research has focused on enhancing engine performance through the use of sophisticated combustion techniques, looking into alternative fuels, and optimizing operational factors in order to get around this problem. Traditional experimental techniques often require significant time and financial commitment, even if they have proven successful. As a result, optimization methods like Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) have gained recognition as practical instruments for enhancing engine performance and reducing emissions (Kolakoti et al., 2023).

Process development, improvement, and optimization can be performed through several powerful statistical and mathematical techniques. Among these techniques (RSM) is recognized as powerful statistical and mathematical technique that is commonly used for process development, improvement, and optimization. RSM is useful to simultaneously optimize conflicting ideas such as minimizing emission and enhancing engine performance at few experimental run (Veza et al., 2023). ANN has special capacity to model complex and nonlinear systems which makes them popular for optimization. Because these networks are adept at finding patterns in big datasets, they can predict outcomes like emissions and engine performance metrics under a variety of operating conditions. Through training on empirical data, ANNs can produce fast and accurate predictions while significantly reducing the need for time-consuming experimental procedures (S. Şahin, 2023). The Objective of this research is to simultaneously improve Deisel Engine performance and Reduce Engine's emission. In this study Diesel engine is run on butanol and diesel mixtures. By applying these techniques, this research will contribute to the development of diesel engines that are more efficient and environmentally friendly.

1.2. Statement of the problem

The rising need for energy and the growing environmental concern over the dangerous emissions from conventional CI engines have prompted a continuous search for alternative fuels and advanced optimization techniques. Due to their excellent fuel efficiency and higher output most of industry and transportation sector uses CI engine. However, harmful gases like NOx, PM, CO, and HC are frequently released by this engine. These gases deteriorate air quality and have significant health problems. To react to this drawback, alternative sources of fuel such as diesel-n-butanol which can improve combustion and reduce emission becoming compulsory. However, because engine parameters behave nonlinearly under different operating situations, maximizing engine performance and reducing emissions with such blends is a difficult task. Conventional experimental techniques for improving engine performance and emissions are labor-intensive, resource-intensive, and frequently unable to fully capture the complex interrelationships between numerous variables. The best way to minimize these difficulties is to use more sophisticated and effective optimization approaches. Therefore, to overcomes these problems the application of sophisticated computational methodologies, specifically response surface RSM and ANN were used to systematically enhance the performance and emission profiles of a diesel engine utilizing diesel-n-butanol blends. These approaches are capable of elucidating the ideal operating parameters that can lead to improved engine efficiency while concurrently reducing emissions. The goal of this work to develop and applying ANN and RSM models to optimize engine parameters and evaluate the environmental benefits of using diesel-n-butanol blends

1.3. Objectives of the study

1.3.1. General objective

The general objective of this study is to obtain the optimized mixing ratios of diesel and n-butanol for better performance and emissions characteristics in diesel engine using response surface methodology and artificial neural network methods.

1.3.2. Specific objective

The specific objectives of this study are:

- To test the performance and emission of CI engine fueled with diesel-n-butanol blends.
- To evaluate the effect of premixing ratio of n-butanol with diesel on CI engine.

- To obtain the optimum premixing ratio of n-butanol with diesel for better performance using optimization methods.
- To compare predictive capability of RSM and ANN using statistical parameters and compare the results with commercial diesel fuel.

1.4. Significance of the study

This study explores the potential of diesel-n-butanol fuel blends as sustainable alternative to conventional diesel, aiming to optimize both performance and emission characteristics of CI engine. The use of advanced optimization techniques, namely RSM and ANN, allows for a comprehensive analysis and accurate prediction of engine behavior under various conditions. The findings of this study are expected to support the gradual transition from fossil fuels to cleaner-burning alternatives, thereby reducing the environmental footprint associated with diesel combustion.

The successful implementation of diesel-n-butanol blends not only contributes to reduction in harmful exhaust emissions, including greenhouses gases, but also enhances engine performance and fuel efficiency. By promoting the use of renewable, oxygenated fuels such as n-butanol, this research supports global efforts toward sustainable energy solutions and energy diversification. Ultimately, the study provides valuable insights for engine designers, fuel researchers, and policy makers interested in balancing energy demand with environmental responsibility.

1.5. Scope of the study

This study investigates the impact of diesel-n-butanol fuel blends on the emission and performance characteristics of a single-cylinder, 4-stroke CI engine. The primary objective is to evaluate how varying proportions of n-butanol blended with commercial diesel influence parameters such as BP, BT, BSFC, and exhaust emissions including NOx, HC, CO, and CO_2 across selected engine load conditions.

The study utilizes RSM for experimental design and process optimization, and ANN for predictive modeling and validation. These tools are used to identify optimal fuel blend ratios and operating conditions for improved engine performance and reduced emissions. However, the scope of this research is limited to performance and emission measurements only. It does not include detailed combustion analysis such as in-cylinder pressure, HRR, combustion duration or ignition delay.

Furthermore, the study does not address long-term engine wear or economic assessments of fuel blending.

1.6. Limitations of the study

Despite the valuable insights gained from this research, several limitations affected the depth and breadth of the investigation. One significant constraint was the inability to measure particulate matter emissions due to the unavailability of a particulate matter analyzer. This restricted the study from providing a comprehensive evaluation of all emissions components, particularly those related to soot and fine particulates. Furthermore, the absence of an in-cylinder temperature sensor prevented the monitoring of real-time combustion chamber temperatures, limiting the study's ability to perform detailed thermal and combustion diagnostics.

Another major limitation was lack of access to a fully equipped automotive laboratory. The university's limited laboratory resources posed challenges in acquiring essential equipment such as a high-precision engine test rig, advanced exhaust gas analyzers, and data acquisition systems. These constraints not only affected the precision and scope of experimental measurements but also limited the opportunity for replicating tests under broader operating conditions. Additionally, the study did not incorporate long term engine durability assessments or the economic feasibility of fuel blends, which could have provided further insights into the practical application of diesel-n-butanol blends in real-world conditions

1.7. Organization of the thesis

This thesis structured into five comprehensive chapters, each addressing a key component of the research process and contributing to a cohesive understanding of the study's objectives.

Chapter One: presets general introduction, including the background of the study, the problem statement, research objectives, scope, significance, and limitations. It outlines the growing concerns associated with diesel engine emissions and the need for cleaner fuel alternatives. The chapter establishes the rationale for blending with n-butanol to enhance performance and reduce harmful emissions in CI engines. It also introduces the use of RSM and ANN as optimization and modeling tools to determine the most effective blending ratios. The chapter sets the stage for achieving improved combustion characteristics and promoting environmentally sustainable fuel practices.

Chapter Two: provides a critical review of the literature relevant to the study. It explores previous research on alternative fuels, particularly n-butanol, and examines the application of RSM and ANN in engine performance modeling and emission optimization. This chapter identifies gaps in the existing body of knowledge and highlights the contributions and limitations of prior work, thereby justifying the need for the present study.

Chapter Three: details the methodology adopted for the experimental work. It includes a through explanation of the experimental setup, blending ratios, engine operating parameters, and the statistical and computational methods used for analysis. This chapter outlines the design of the experiments using RSM, the data collection process, and the structure of the ANN models used for prediction and validation.

Chapter Four: presents the experimental results and discusses the key findings. It includes data analysis, graphical representation of performance and emission trends, and comparative evaluations of the different diesel-n-butanol blend ratios. The chapter provides scientific interpretations of the observed effects and assesses the predictive capabilities of RSM and ANN models.

Chapter Five: concludes the thesis by summarizing the major findings and their implications. It offers practical recommendations for the use of diesel-n-butanol blends in CI engines. Finally, the chapter suggests directions for future research, including extended combustion analysis, engine durability testing, and broader fuel blend evaluations under real-world conditions.

CHAPTER TWO

LITERATURE REVIEW

The increasing environmental issues and the diminishing fossil fuel reserves have prompted extensive research into alternative fuels and optimization methods for ICEs. Among the different alternative fuels, alcohol-based options such as n-butanol have attracted interest because of their renewable characteristics, oxygen content, and ability to lower harmful emissions when mixed with diesel. In addition, sophisticated modeling and optimization techniques, including RSM and ANN, are being more frequently utilized to examine and enhance engine parameters for better performance and a lesser environmental footprint.

2.1. n-Butanol as an alternative fuel

Alcohol can be mixed with fossil diesel and other alternative fuels to improve engine performance and emissions. Several studies have determined that n-Butanol is a top fuel additive for reducing air pollution and increasing diesel engine efficiency. This substance is categorized as a toxic alcohol and can be obtained from unusual sources. Because of its low cetane number, high volatility, viscosity, and more oxygen supply, n-butanol can be easily mixed with regular diesel (Mahla et al., 2023).

n-Butanol is an alcohol-based fuel, just like methanol and ethanol. Ethanol is the most widely used alternative fuel in ICEs. Some nations, like Brazil, have completely embraced ethanol as a fuel for internal combustion engines. Studies show that butanol, which can be used in ICEs, has better qualities than ethanol. Studies have demonstrated that butanol is a renewable alternative fuel with many promising uses for internal combustion engines, even though it isn't currently used commercially in the automotive industry. Fermentation of biomass feedstock is one common process for producing butanol. Butanol has four isomers: s-butanol, n-butanol, iso-butanol, and tert-butanol. Nowadays, it's likely that the isomers iso-butanol and n-butanol are used as biofuels. Because the butanol isomer degrades much more slowly than the other fuels, its use is not widely recognized.

Because it blends well and is easy to mix with gasoline, n-butanol is the most beneficial fuel of all the butanol isomers. Furthermore, because butanol is an alcohol fuel with an oxygen concentration that is very helpful in reducing soot formation a major issue for CI engines. It presents an opportunity to use it in diesel-blended CI engines. The issue of NOx emissions from diesel engines can also be resolved by lowering the combustion temperature. Because butanol has a higher HLV than ethanol, it lowers the ignition temperature and offers an opportunity to control NOx emissions. Bio-butanol can be used as fuel in SI engines and as an oxygen enhancer when combined with gasoline. Diesel and n-butanol blends can also be used in CI engines due to their distinct characteristics, particularly their cetane number, which is comparable to that of pure diesel. Butanol is a contender for the position of alternative fuel of the future because of all these benefits over other alcohols (Gwalwanshi et al., 2022).

2.1.1. Production of n-butanol

Particularly in the last few years, experts studying internal combustion engines and the automotive sector have been more interested in butanol. The tightening emission regulations, rising costs for traditional fuel, and the depletion of conventional fuel sources are the causes of this increased interest in butanol. The availability and manufacturing of butanol have come under scrutiny due to its potential as an engine fuel. Petro butanol, derived from fossil fuels, or bio-butanol, derived from biomass, can be used to produce butanol (Maiti et al., 2016). Despite the differences in their methods of manufacturing, both varieties have the same chemical attributes (da Silva Trindade & dos Santos, 2017). Furthermore, biobutanol is a second-generation alcohol fuel. Crop residues, agricultural waste, and non-edible oil are examples of non-food crops that are used to make second-generation biofuels (Naik et al., 2010). Thus, the main source of 2nd-generation biofuel feedstock is non-edible food crops waste (Begum & Dahman, 2015). Among the currently utilized biofuels, first-generation biofuels like ethanol and biodiesel are also highly popular; nevertheless, the primary feedstock for these biofuels is food grains like corn and wheat. Because the feedstock for first-generation biofuels is human food, there needs to be less reliance on them (Begum & Dahman, 2015).

The most appealing technique for producing biobutanol is the ABE fermentation strategy, which ferments carbohydrates to produce acetone, butanol, and ethanol as the main byproducts (Veza, Said, et al., 2021). Both acetic and butyric acids are produced during the first stage of fermentation, which is a growth stage. The second stage of fermentation is characterized by the reassimilation of acids into acetone, butanol, and ethanol in a mass-ratio of 3:6:1 (da Silva Trindade & dos Santos, 2017). The production process can have an impact on the isomers of butanol produced. A basic schematic of the process for producing bio-butanol can be found in Figure 2.1. This technique involves pretreating the biomass feedstock in the first step, followed by detoxification to get rid of anything undesired that can interfere with the chemical reaction (Baral & Shah, 2014). The type of feedstock taken into consideration and the pretreatment method have an impact on the detoxification. The most crucial phase in the process of producing butanol is fermentation, which comes next. The process is known as the ABE method, and it produces a mixture of acetone, butanol, and ethanol. The final step involves the separation of every component at the boiling point by a process of distillation and purification. Acetone, butanol, and ethanol have respective boiling points of 56 °C, 118 °C, and 78 °C (Huang et al., 2015).

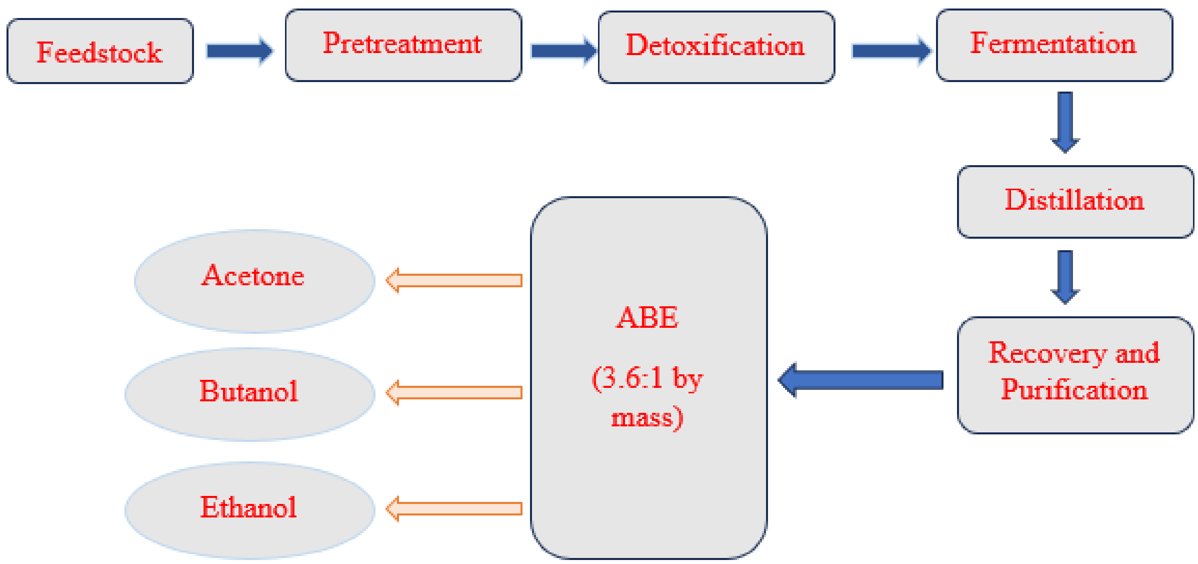


Figure 2.1 A simple diagram of ABE for bio-butanol production

2.1.2. Features of n-butanol

n-butanol has the potential to be the future generation of alternative bio-based fuel since its superior properties over other alcohols. The main features of n-butanol, other alcohols, and fossil fuels are shown in Table 2.1 to aid in comprehension of the substance's properties. The main features of both conventional fuels, such as gasoline and diesel, and biofuels, such as methanol, ethanol, and n-butanol, are displayed in Table 2.1. The following assertions can be backed up by this table. N-butanol is a fuel with a higher resistance to friction because it is more viscous than other alcohols. Certain parts of the engines' cylinders come into direct contact with engine fuel when the engines are operating. If the fuel in the engine has a high enough viscosity, it can reduce the effect of friction between its different parts. Furthermore, n-butanol's low enthalpy of vaporization may lessen the importance of the cold start issue. Compared to other alcohol fuels, n-butanol has a higher carbon content, which makes it less volatile and safer for transportation. Furthermore, n-butanol will likely show better fuel efficiency because it has a much higher energy density than other alcohol fuels (Gwalwanshi et al., 2022).

Table 2.1 Properties of conventional fuels and various alcohol

Parameter	Diesel	Gasoline	n-butanol	Methanol	Ethanol
Molecular formula	C_{12}-C_{15}	C_4-C_{12}	C_4H_9OH	CH_3OH	C_2H_5OH
Density (kg/m^3) at 20^{o}C	810-890	720-780	808-810	790-796	785-794
Molecular weight	198.4	111.19	74.11	32.04	46.06
Auto-ignition temp (^{o}C)	210-250	300	385-397	463-470	423-434
Viscosity (mm$^{2/}$s) at 40^{o}C	1.9-4.10	0.4-0.8	2.63-3.70	0.58-0.59	1.08-1.20
Cetane number	40-55	0-10	17-25	3-5	5-8
Octane number	20-30	80-99	96	111	108
Oxygen content (weight %)	-	-	21.6	50	34.8
Lower heating value (kJ/kg)	270	380-500	582	1109	904
Energy density (MJ/L)	35.86	32	29.2	16	19.6

2.2. Effect of Blended Diesel/n-butanol on Performance and Emissions of a CI Engine

2.2.1. Performance characteristics of diesel/n-butanol blend

In order to assess its different performance characteristics, n-butanol has been added to fuels. Table 2.2 summarizes the performance characteristics of a CI engine fueled by n-butanol blends as determined by diesel engine experts. Table 2.2 shows that for all blended fuel types, the brake thermal efficiency decreases, resulting in an increase in brake fuel consumption for all loads in order to produce the same power output. This phenomenon can be attributed to the considerable decrease in the calorific value of butanol fuel, which is approximately 33 MJ, in contrast to 44 MJ for fossil diesel and 42 MJ for biodiesel fuel.

(Wakale et al., 2018) As shown in Figure 2.2, distinct fuel mixtures B5, B10, and B20, which are n-butanol mixed with pure diesel in a bi-fuel engine, showed a decrease in BSFC when the engine ran on a fuel blend containing 5% n-butanol as opposed to fossil diesel. Additionally, BTE showed comparable results for the fuel blends B10 and B20. This finding can be explained by the B5 fuel blend's lower equivalency ratio compared to all other fuel types.

(Algayyim et al., 2017) found that using n-butanol fuel blends instead of conventional fossil diesel decreased engine torque and blood pressure. The main reason for this decrease is that n-butanol has a Lower CV than fossil diesel. However, when compared to fossil diesel, the higher BTE was justified by the improved combustion efficiency and quick energy release brought about by improved mixture of air-fuel and the ID delay linked to n-butanol. Furthermore, compared to fossil diesel, the BSFC showed an increasing trend throughout the whole range of n-butanol fuels. This is because higher alcohols have a lower energy content.

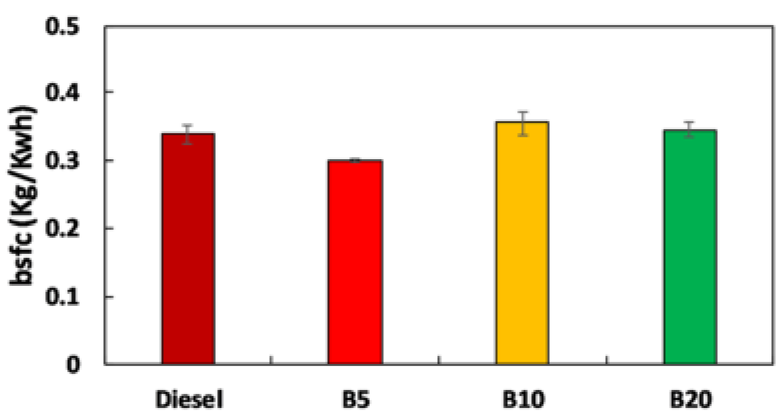


Figure 2.2 BSFC of pure diesel, B5, B10, and B20 (Wakale et al., 2018)

(Çelebi & Aydın, 2018) examined the impact of adding n-butanol to biodiesel when utilized in a CI engine that powers an electrical generator. Biodiesel was produced through the transesterification process. Butanol-biodiesel binary blends and ultra-low sulfur diesel-biodiesel-butanol ternary blends with 5%, 10%, and 20% by volume were used in the study. A multi cylinder, 4 -stroke, DI diesel engine running at half load and a constant engine speed of 1500 rpm was used for testing. The fuels' performance, emissions, and combustion characteristics were the main focus of the experimental findings. The results showed that while total heat transfer total, gas temperature gas and mass fraction burned showed only minor variations, the HRR and in-cylinder pressure curves were noticeably similar. The ternary blends showed a 1.5% increase in BTE and decreased emissions. Additionally, BSFC increased by up to 6% and average MFC increased by up to 5%. In contrast, the other fuels experienced a decline in both emissions and BTE.

(Yesilyurt et al., 2018) tested a diesel engine's performance with biodiesel and n-butanol fuels. In contrast to diesel fuel, the researchers found that the engine's BP reduced as the amount of n-butanol in the fuel blend enhanced (Figure 2.3). This phenomenon was explained by the longer ignition lag and low energy content of n-butanol. Additionally, compared to baseline diesel, the fuel's BSFC increased when n-butanol was added. This finding was associated with n-butanol's lower heating value compared to pure diesel. Furthermore, since methyl esters are categorized as oxygenated fuels, an enhance in BTE values was noted for n-butanol fuel blends relative to fossil diesel.

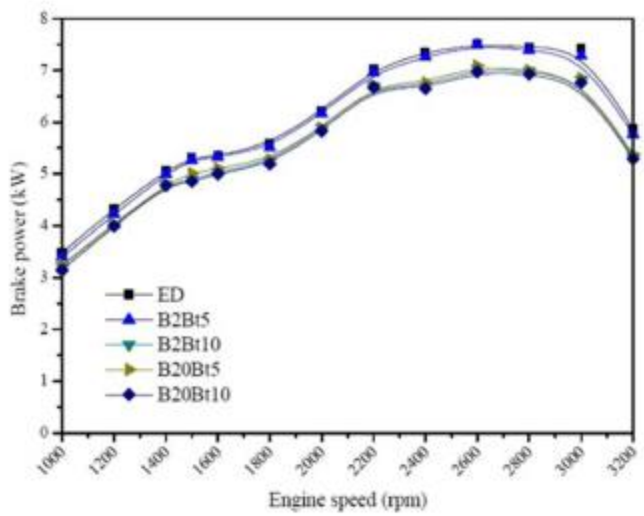


Figure 2.3 variation of BP with speed (Yesilyurt et al., 2018)

(Huang et al., 2017) studied impact of adding PODE3-4 to CI on the characteristics of spray was examined within a CV spray chamber at various injection pressures. The performance of the engine and the emission characteristics of n-butanol/PODE3-4/diesel blends were analyzed in a CI engine operating under high injection pressures. The findings reveal that the spray penetration of PD20 and BD20 exceeded that of D100; furthermore, the incorporation of PODE3-4 into BD20 resulted in an additional increase in spray penetration, while not significantly affecting the spray cone angle. At a consistent fuel injection pressure, the combustion of BD20 exhibited the highest MPRR, which diminished following the addition of PODE3-4 to the blend. The emissions of NOx and soot from BD20 were lower compared to those from pure diesel. In comparison to BD20, the combustion of BDP20 achieved reductions in HC and CO emissions of up to 28.24% and 45.65%, respectively. The emissions of NOx, soot, HC, and CO from BDP20 were all lower than those from PD20. As the fuel IP increased, a downward trend was noted in both the number concentration and the mass concentration of total particles. The lowest emissions in terms of total particle mass concentration were recorded for BDP20, followed by PD20, BD20, and D100. The proportion of sub-50 nm particles to total particles was highest for BD20, irrespective of the injection pressure, and this ratio decreased with the addition of PODE3-4 to BD20.

(Jeevahan et al., 2018) diesel engine was operated using a mixture of n-butanol and diesel. The BTE exhibited a decline as the concentration of n-butanol in the fuel blends increased. This reduction in BTE can be attributed to the elevated heat consumption resulting from the high heat of vaporization associated with n-butanol. Consequently, this factor contributes to the diminished BTE. Additionally, the combustion efficiency of the engine is adversely affected by the presence of n-butanol, primarily due to its low CN; this serves as a secondary factor leading to the reduced BTE. Furthermore, the significant LHV of n-butanol has been linked to an enhance in BSFC for blend of n-butanol when compared to fossil diesel, as it absorbs a greater amount of heat during the combustion process. However, as the proportion of n-butanol in the fuel blends is increased, the BSFC tends to decrease. This reduction is due to the lower viscosity and more oxygen content of n-butanol, which facilitates more complete combustion and, as a result, leads to a decrease in BSFC.

Table 2.2 Performance characteristics of CI engines fueled with n-butanol blends

References	Fuel used	BP	BTE	BSFC	Optimized parameter
(Gautam & Kumar, 2015)	JEE5Bu15D80, JEE10Bu10D80 JME5Bu15D80, JME10Bu10D80	↓	↑	↑	JME10Bu10D80
(Atmanlı et al., 2015)	D60B10nBu30, D50B30nBu20, D30B30nBu40, D30B10nBu60, D20B20nBu60	↓	↑	↑	D60B10nBu30
(Jindal et al., 2015)	nbu10B10, nbu20B20	↓	↑	↑	nbu10B10
(Rakopoulos et al., 2011)	D92nB8, D84nB16	-	↑	↑	D84nB16
(Atmanli & Yilmaz, 2018)	DnB5, DnB25, DnB35	-	↓	↑	DnB25
(Al-Hasan & Al-Momany, 2008)	D90nB10, D80nB20, D70nB30, D60nB40	↓	↓	↑	D70nB30
(Rakopoulos et al., 2010)	D92nB8, D84nB16, D76nB24	-	↑	↑	D84nB16
(Chen et al., 2013)	D80nB20, D70nB30, D60nB40	-	↑	↑	D80nB20

2.2.2. Emission characteristics of diesel/n-butanol blend

n-Butanol has been investigated as a potential alternative fuel that may help mitigate the severe pollution caused by harmful gases. The emission characteristics of n-butanol, as assessed by several researchers, are detailed in this document. Table 2.3 illustrates a variety of emission characteristics of the CI engine when different blends of n-butanol were utilized as fuel. Table 2.3 presents the varying results by examining the emission characteristics in terms of HC, CO, smoke, and NOx. It is evident that HC, CO, and soot levels decreased for all fuels tested, while the reduction in NOx exhibited a mixed pattern; biodiesel fuels showed an increasing trend, whereas neat butanol demonstrated a reducing trend. This phenomenon can be attributed to the impact of butanol's addition to the diesel fuel solution, which leads to a decline in the cetane rating and a reduction in heating values.

(Bitrus et al., 2020) impacted a study on the impact of butanol addition to diesel/ biodiesel blend to evaluate the emission characteristics of a CI engine. The experiments were performed using a 4-stroke, single-cylinder, air-cooled CI engine. A blend consisting of 20% neem biodiesel and 80% diesel fuel was created and designated as B20. Subsequently, butanol was incorporated into the B20 blend at volume percentages of 15%, 10%, and 5%, labeled as B20Bu15, B20Bu10, and B20Bu5, respectively. These samples underwent testing on the engine under two conditions: first, at a constant speed of 2600 rpm with varying torque values of 11, 10, 8,6, and 4 Nm; and second, at a constant torque of 4 Nm with varying speeds of 2600, 2400, 2200, and 2000 rpm. An EGA was utilized to assess exhaust emissions, including NO, CO_2, CO, and HC. The findings indicated that the B20 blend exhibited the highest NO emissions across all engine loads. At varying speeds, the B20 blend averaged NO emissions of 303.8 ppm, while the addition of butanol to the B20 blend led to a significant reduction in NO emissions by 16% as depicted in Figure 2.4. The reduction in NO emissions was more pronounced with an increased % of butanol in the blend. Regarding CO_2 emissions, it was observed that blends containing butanol emitted higher levels of CO_2 compared to the B20 blend. Nevertheless, CO_2 emissions decreased as the percentage of butanol in the blend increased. At a constant speed, the B20 blend produced higher CO emissions than the blends containing butanol, whereas at varying speeds, the differences were negligible. Additionally, it was found that blends with butanol released higher HC emissions than the B20 blend across all engine speeds. At varying torque, the B20 blend emitted higher HC levels than the butanol blends, except for B20Bu15, which averaged 16.4 ppm.

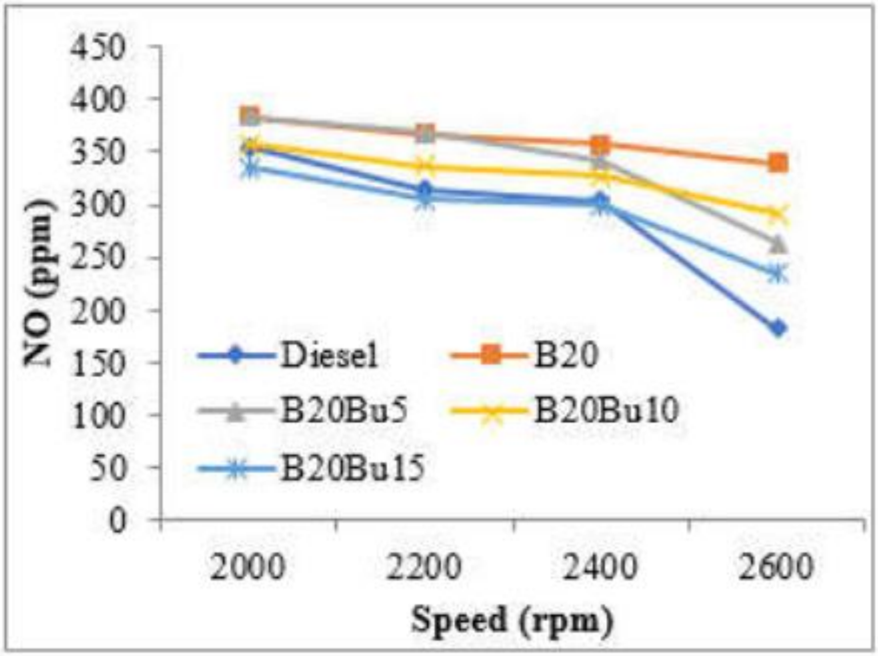


Figure 2.4 Nitric oxide Vs engine speed

(Z. Şahin & Aksu, 2015) employed a CI engine and performed experiments at engine speeds (2000) rpm (with engine loads of 132 and145 Nm) and 4000 rpm (with engine loads of 96 and100 Nm) to assess the emission characteristics of the engine utilizing n-butanol fuel blends. Under specific load and \speed, it was observed that NOx emissions were lowest with nB2 blends compared to all other fuels tested. The increase in excess air coefficients within the engine cylinder was found to be less effective in reducing combustion temperature, which was the primary factor contributing to the lower NOx emissions associated with nB2. In contrast, nB4 and nB6 blends exhibited an increase in NOx emissions compared to diesel. The fuel blends with n-butanol demonstrated a lower viscosity than conventional diesel, leading to a reduction in fuel droplet size and consequently an increase in NOx emissions. The authors attributed the greater HC emissions detected with n-butanol blends, in comparison to diesel, to the same underlying reason. It was concluded that CO_2 emissions were elevated with n-butanol when compared to diesel, due to the greater oxygen content in n-butanol, which facilitated complete combustion. Additionally, due to the low CN of n-butanol, smoke emissions from blends containing n-butanol exhibited reduced smoke opacity when compared to diesel (Figure 2.5).

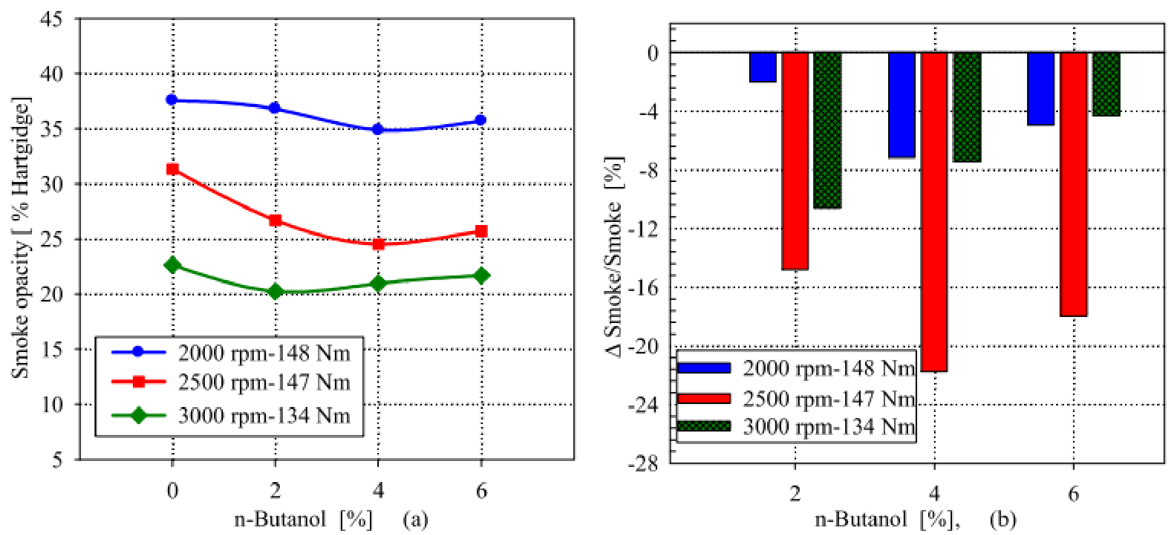


Figure 2.5 (a and b) Variation ratios of smoke Vs n-butanol ratios for different loads and speeds respectively.

(Algayyim et al., 2017) noted a reduction in HC emissions when using blends of n-butanol compared to diesel. The increased LHV associated with n-butanol was found to contribute to this reduction in HC emissions. Additionally, NOx emissions were noticed to slightly decline with the incorporation of n-butanol in fuel blends relative to diesel. This effect was ascribed to the more oxygen content and LCT present in n-butanol. Furthermore, CO_2 emissions exhibited a downward trend across the entire spectrum of fuel blends containing n-butanol when compared to diesel at low engine speeds. This phenomenon was explained by the formation of a lean mixture at lower speeds. Conversely, at higher speeds, an increase in CO_2 emissions was recorded for butanol blends, which was due to the elevated oxygen levels in the fuel blends containing n-butanol.

(Çelebi & Aydın, 2018) conducted experiments to examine the emission characteristics of fuels blended with n-butanol. It was notice that blends of n-butanol resulted in lower CO emissions and higher CO_2 emissions, attributable to the greater oxygen content in n-butanol compared to diesel. The researchers determined that this same factor contributed to the decrease in HC emissions and the increase in NOx emissions when using n-butanol blends as opposed to diesel.

(Yesilyurt et al., 2018) conducted experiments to determine the emission characteristics of a CI engine. The higher oxygen content of n-butanol lead to more complete combustion of the fuel in cylinder. Consequently, the authors reported that blends of n-butanol fuel produced lower CO emissions and reduced smoke opacity compared to fossil diesel. Researchers provided the same rationale for the observed increase in O_2 emissions in blends containing n-butanol when compared to fossil diesel. In terms of CO_2 emissions, a reduction was observed when utilizing n-butanol fuel blends in contrast to diesel. The authors explained this unexpected finding by noting that the molecular structure of alcohols contains fewer carbon atoms than diesel. Additionally, NOx emissions were found to decrease when using n-butanol fuel as opposed to diesel, attributed to the cooling effect of alcohols, which lowered the in-cylinder temperature, thereby reducing the combination of nitrogen and oxygen atoms.

(Huang et al., 2017) investigated the emission characteristics of a CI engine and observed that, in comparison to fossil diesel, the addition of n-butanol to the tested fuel resulted in a reduction of soot emissions. This reduction can be ascribed to the oxygenated nature of n-butanol. Furthermore, it was noted that NOx emissions also decreased when using a B20 fuel blend as opposed to pure diesel. This decrease is due to the shorter ID period and the lower CN of n-butanol, which contribute to a reduction in combustion pressure and temperature within the cylinder. However, the increase in HC and CO emissions (as illustrated in Figure 2.6) for n-butanol blends, when compared to baseline diesel, can be explained by the highly volatile characteristics of n-butanol. This volatility leads to a more amount of fuel being injected into the crevice and boundary layer of the cylinder wall.

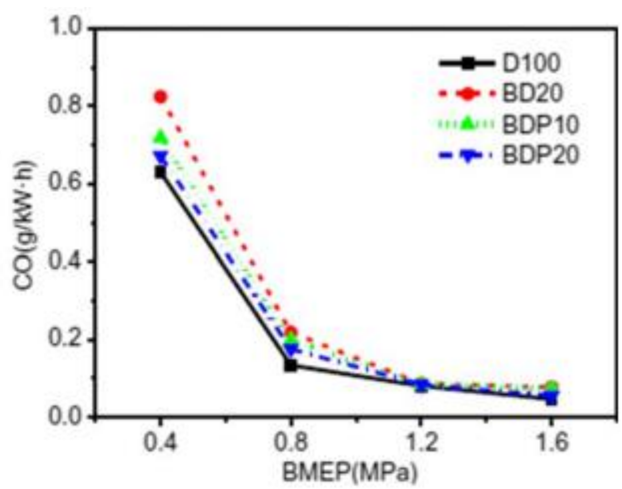


Figure 2.6 CO deviation emissions with BMEP

(Huang et al., 2016) conducted a study in which they combined diesel, gasoline and n-butanol, utilizing EGR, and subsequently tested this mixture on a CI engine to assess the engine's emission characteristics. It was observed that the soot, HC, and CO remained relatively stable regardless of the fuel composition, consistently exhibiting low levels; however, when the EGR ratio exceeded 25%, an increase in the EGR ratio led to a significant rise in the soot, HC, and CO produced by the four fuels, while NOx experienced a decline, nearing zero as the EGR ratio approached 40%. At these EGR levels, the blended fuels that included n-butanol demonstrated a more pronounced reduction in soot production compared to the fuels that contained gasoline. Furthermore, NOx emissions were found to be more significantly affected by the EGR ratio than by the combustion characteristics, as illustrated in Figure 2.7.

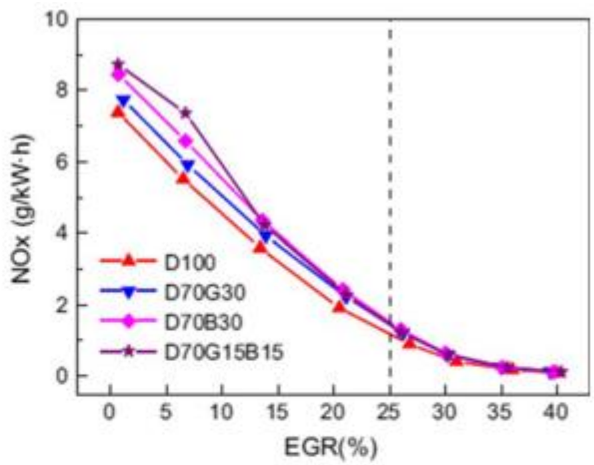


Figure 2.7 Variation of NOx with EGR

(Mohebbi et al., 2018) employed a modified CI engine and observed a decrease in CO when n-butanol was added to the tested fuels compared to diesel. This reduction is ascribed to the improved premixed HRR, as n-butanol contains a greater amount of oxygen. Furthermore, n-butanol possesses a high LHV, which results in a LTC. This phenomenon was identified as a significant factor contributing to the increase in HC emissions for B40 and B20 when compared to diesel.

Table 2.3 Comparative analysis of emissions from CI engines fueled with n-butanol Blends

References	Fuel used	CO	CO_2	HC	NOx	smoke	Optimized parameter
(Sivasubramanian, 2018)	D85B10 P5, D80B10P10, D75B10P15	↓	-	↓	↑	↓	D80B10P10
(Jindal et al., 2015)	nbu10B10, nbu20B20	↓	-	↓	↑	-	nbu10B10
(Meirs et al., 2008)	D80nB20, D60nB40	↑	-	↑	↑	-	D80nB20
(Atmanli & Yilmaz, 2018)	DnB5, DnB25, DnB35	-	↓	↑	↓	-	DnB25
(Liu et al., 2013)	D80nb20	↑	-	↑	↓	-	D80nb20
(Huang et al., 2019)	BD20, BDP10, BDP20	↑	-	↑	↑	↓	BDP20
(Huang et al., 2016)	D70G30, D70B30, D70B15G15	↓	-	↓	↑	↓	D70B30
(Satsangi et al., 2016)	D95nB5, D90nB10, D85nB15, D80nB20	↓	-	↑	↓	↓	D90nB10
(Chen et al., 2013)	D80nB20, D70nB30, D60nB40	↓	-	↑	-	↓	D80nB20

2.2.3. Summary of emission and performance characteristics of diesel/n-butanol blend

A review of the literature indicates that n-butanol can readily blend with both diesel and biodiesel. The following conclusions can be drawn from the cited literature regarding the emission and performance characteristics of engines when compared to pure diesel:

- The lower CV, along with the increased ID and HLV of n-butanol, results in a higher BSEC and BSFC, while simultaneously leading to a decrease in BP and BTE when n-butanol is utilized as fuel in the engine, as opposed to fossil diesel.
- In general, it has been observed that NOx emissions are lower when using n-butanol fuel blends compared to baseline diesel. This phenomenon can be ascribed to the lower viscosity and higher LHV of n-butanol, which facilitates improved atomization and consequently reduces the combustion temperature.
- Due to the higher oxygen content in n-butanol, it facilitates a more complete combustion of fuel, resulting in a reduction of CO and smoke opacity, while CO_2 and O_2 emissions tend to be elevated, as noted by numerous researchers.
- Furthermore, HC emissions rise as a consequence of the high volatility and low CN associated with n-butanol.

2.4. Optimization Techniques

Optimization is the process of selecting the process parameter to produce the desired result. Under a variety of restrictions, optimization determines the optimal answer for the given aim. Single-objective and multi-objective optimization are both possible. Two approaches can be used for optimization. First, the global maxima or minima in the plotted result can be located using the graphical method. The latter is the gradient approach, which determines the maximum or lowest gradient by utilizing the gradient of the objective function. In the search space or design space of the design vector, the two approaches locate the maxima or minima. a number of forecasts and optimization strategies were used to look at the emissions and engine performance. One tool for prediction and optimization used to examine engine characteristics is response surface methodology (Sakthivel et al., 2021).

2.4.1. Response surface methodology (RSM)

RSM serves as a widely utilized experimental design approach for the exploration and modeling of processes. It stands out as an exceptionally effective technique for the multivariate analysis of responses, offering enhanced error management across various conditions. This robust statistical method enables the examination of how different input factors affect output variables. Consequently, through the optimization process, RSM significantly minimizes the time, materials, and costs associated with performing multiple trials (Abdullahi et al., 2023).

RSM is a sophisticated mathematical and statistical approach employed in the design of experimental studies. Its primary objective is to enhance the response variable that is influenced by several independent factors. The second-order polynomial equation presented in Equation (2.1) serves as a predictive model for the output response, incorporating the various input variables into its formulation (Veza et al., 2023).

$$Y = b_0 + \sum_{i=1}^{k} b_{i\,x_i} + \sum_{i=1}^{k} b_{iix_i^2} + \sum_{i<1}^{k} b_{ijx_{ixj}} + e \qquad (2.1)$$

Where Y is the response; $x_i$and x_j are factors; b_i and b_{ii} are the 1st order and the 2nd order coefficients, respectively; b_0 denotes the intercept; b_{ij} is the model linear coefficients (for the *i* and *j* variables); k is the number of factors studied in the experiment and *e* is the error related with output.

The initial and most crucial phase in the application of RSM involves the careful selection of input or independent variables, as these elements play a pivotal role in influencing the entire process, including the resultant outputs. A review of existing literature on the implementation of RSM in ICEs operating on alternative fuels reveals that the independent variables typically encompass operational parameters such as engine load, speed, CR, and blending ratio. It is essential to judiciously determine the ranges for these selected factors, which are generally informed by prior experimental findings. Inadequate selection of the independent variables and their corresponding ranges can lead to results that are both inaccurate and of limited utility. Furthermore, it is imperative to identify desirable outputs that significantly affect engine performance, combustion efficiency, and emission profiles. Consequently, the foremost task prior to employing the RSM technique is to methodically establish the independent factors and the desired responses in a manner that is both logical and effective (Alhassan et al., 2016).

2.4.2. Response surface design for RSM

Response surface design encompasses a collection of sophisticated DOE techniques aimed at optimizing specific responses. Following the identification of factors and responses, the subsequent essential phase involves the strategic design of experiments, which entails selecting the experimental points where the anticipated responses can be accurately predicted and assessed. Upon identifying the number of factors at play, different DOE methodologies can be developed to create a response surface. These designs are classified based on their essential attributes, including variance and the overall count of experiments performed (Ahmad et al., 2024). he selection of an appropriate design strategy is crucial to the overall experimental process. Nevertheless, it is noteworthy that many previously published studies inadequately justify their choice of response surface design, often providing only cursory explanations. Response surface design encompasses three primary categories: FFD, CCD, and BBD. In the context of experimental design, a factor is defined as a variable that can affect the system's or process's response. The levels of a factor denote the various values or settings applied during the experiment. Understanding the concept of levels is essential, as it enables researchers to systematically investigate the interplay between factors and responses across a spectrum of conditions. The selection of levels for a factor is contingent upon the specific objectives of the experiment and the anticipated range of influence on the response. By strategically choosing these levels, researchers can examine how temperature, for instance, affects the response variable at various points within the designated range. It is vital to select suitable levels for each factor to ensure that the experiment yields relevant data and valuable insights. The levels should encompass a range that accurately reflects practical operating conditions or the area of interest. Furthermore, the number of levels selected for each factor can significantly influence the precision and accuracy of the experimental outcomes, necessitating a careful determination of an adequate number of levels to effectively capture the response variable's behavior across the factors' range (Karchiyappan & Karri, 2021).

A) Full factorial design (FFD)

A RSM experiment utilizing a FFD examines every possible combination of factor level. This approach necessitates that at least one trial is conducted for each conceivable combination of factors and their respective levels, thereby ensuring that all interactions among factors are accounted for. The total number of trials or repetitions is a pivotal aspect of the experimental design, influenced by various elements such as the required accuracy of the results, the inherent variability of the data, and the resources available, including time and materials. By increasing the number of repetitions, researchers can mitigate the effects of random variation, leading to a more accurate estimation of the factors' true effects. It is crucial to document the number of repetitions employed in the study, as this information reflects the reliability and robustness of the experimental outcomes. However, practical limitations may restrict the ability to perform a large number of repetitions, necessitating an acknowledgment of these constraints and their potential impact on the precision and generalizability of the results. Consequently, the implementation of FFD can be relatively costly and time-intensive, particularly as the number of factors and levels escalates (Veza et al., 2023).

B) Central composite design (CCD)

RSM employing a CCD is widely recognized as a predominant approach in experimental design. CCD is particularly advantageous for sequential experimental investigations, as it allows for the enhancement of previous factorial experiments by incorporating additional axial and center points. This design facilitates the effective approximation of both first and second-order terms, enabling the modeling of a response variable that exhibits curvature through the integration of center and axial points into a factorial framework. The curvature of the response surface can be assessed by utilizing points situated at the midpoint of the experimental domain alongside "star" points positioned outside this domain. In a factorial design, the levels of the points are set at ± 1, whereas the "star" points are designated at $\pm\alpha$, where $|\alpha|$ is greater than or equal to 1. The value of the α parameter is determined based on the computational capabilities and the desired accuracy of the response surface estimation. The efficacy of predictions is influenced by the spatial arrangement of these points, highlighting the significance of the α value and the number of trials conducted at the center of the domain in determining the precision of the estimations (Veza et al., 2023).

C) Box-Behnken design (BBD)

Another variant of response surface methodology is referred to as BBD. This design type is distinct from factorial designs, as it does not rely on either full or fractional factorial approaches. The BBD is particularly advantageous for estimating first- and second-order coefficients due to its typically reduced number of design points, which can lead to significant savings in both time and cost. However, it is important to note that BBD lacks the inherent factorial structure found in CCD, making it less suitable for experiments that require a chronological approach. Despite its limitations in covering the corners of the nonlinear design space, BBD is often regarded as more effective than other response surface designs, such as three-level FFD and CCD. It allows for the exploration of higher-order responses with fewer experimental runs compared to traditional factorial methods. Like CCD, BBD is designed to maintain a higher-order surface by strategically selecting runs and is characterized by its rotatability and the necessity for three levels per factor, enabling it to fit a full quadratic model of the response surface (Veza et al., 2023).

2.5. RSM for ICE-powered with biofuel

Biodiesel is widely recognized as one of the most prominent biofuels globally. The exploration of biodiesel has a rich historical background. In comparison to bio alcohol, biodiesel exhibits superior characteristics such as a higher CN, increased viscosity, elevated flash point, and enhanced lubricity, which collectively render it more appropriate for use in CI engines. (Simsek & Uslu, 2020) employed RSM to enhance the operational parameters of a CI engine running on a blend of safflower, canola, and waste vegetable oil biodiesel. The findings indicated that an load of 1484.85 kW and an IP of 215.56 bar, when utilizing a biodiesel blend ratio of 25.79%, yielded optimal performance metrics. These metrics included a BTE of 20.54%, an EGT of 199.88 °C, a smoke emission level of 0.26%, NOx at 558.44 ppm, and CO_2 emissions at 4.52%. While biodiesel is often regarded as a leading biofuel option, its use is primarily confined to diesel engines. In contrast, alcohol-based fuels like ethanol and n-butanol present greater versatility and demonstrate substantial reductions in emissions under real-world driving conditions (Veza, Roslan, et al., 2021). (Elumalai et al., 2021) reported that blends of alcohol and diesel fuel may lead to a reduction in exhaust smoke compared to biodiesel during transient operating conditions, despite maintaining equivalent oxygen levels. Furthermore, for these blends to be effectively utilized in CI engines, the incorporation of cetane enhancers or the use of glow plugs may be necessary, in addition to an enhance in the engine's CR to facilitate ignition.

In contrast to shorter-chain alcohols like ethanol and methanol, longer-chain alcohol fuels exhibit superior characteristics in terms of CV, flash points, lubricity, CN, and their solubility in diesel fuel. However, their CN are generally lower than those of conventional diesel fuels, necessitating the blending of these alcohols with fuels that possess cetane numbers similar to that of diesel. One potential solution to this issue is the incorporation of HVO or DTBP into the fuel mixture. Furthermore, while n-butanol has been the subject of considerable research in the context of diesel engines, the application of iso-butanol remains largely unexplored (Veza et al., 2023). (Saravanan et al., 2017) employed RSM to enhance the operational parameters of diesel engines utilizing iso-butanol-diesel fuel blends. The primary goal of this research was to achieve a reduction in NOx and smoke emissions while maximizing BTE and minimizing BSFC. The findings from the RSM indicated that the optimal engine settings involved injecting iso-butanol-diesel blends at a pressure of 240 bar, with an injection timing of 23 degrees crank angle before TDC, alongside a 30% EGR rate. These results were corroborated through experimental validation, revealing a prediction error of less than 4%. It is noteworthy that the influences of EGR and injection timing are closely aligned, resulting in similar NOx emissions. Furthermore, even minor adjustments in injection pressure can significantly impact combustion characteristics and, consequently, emissions. While the graphical representations of NOx emissions may suggest similarity, a detailed numerical analysis is essential to uncover any underlying trends or variations that may be quantitatively significant. Additionally, the limitations of the experimental setup and the sensitivity of the measurement techniques must be acknowledged, as the accuracy and precision of the instruments used to measure NOx emissions can introduce uncertainties, potentially obscuring minor emission changes. In conclusion, the application of RSM for biofuels in ICE is summarized in Table 2.4, highlighting the growing interest in bio alcohols and biodiesel due to their potential for production from cost-effective resources and their capacity to significantly mitigate harmful emission

Table 2.4 Summary of RSM application in ICE fueled with biofuel

Type of Fuel	Type of Engine	RSM design	Input factor	Response	Authors
diesel / Iso-butanol blends	CI	3 × 3 FFD	IP, IT, and EGR rate	NOx, CO_2, BTE, BSFC, smoke	(Saravanan et al., 2017)
Diesel/ n-octanol blends	CI	3 × 3 FFD	Blend percentage, IT, EGR	smoke, NOx, BTE BSFC	(Gopal et al., 2018)
Isopentanol-gasoline blends	SI	CCD	CR, fuel ratio, engine speed	BMEP, BTE, BSFC, NOx, CO, HC	(Uslu & Celik, 2020)
Fusel oil-gasoline blends	SI	-	Speed, Load, fuel %	NOx, CO, HC, BP, BSFC	(Awad et al., 2017)
n-butanol-diesel blends	CI	3 × 3 FFD	IT, EGR rate, type of alcohol	Smoke, NOx, CO, HC BSFC and BTE	(Krishnamoorthy et al., 2018)
Sunflower, soybean biodiesel blends	CI	BBD and CCD	blend ratio and load	NOx, HC, BTE	(Elkelawy et al., 2020)

Pongamia biodiesel blends	CI	CCD	Blend ratio, load, IT, IP	NOx, HC, BTE	(Singh et al., 2018)
Argemone Mexicana biodiesel/diesel blends	VCR	D-optimal	Load, blend ratio CR	BTE. BSFC, HC, CO, NOx	(Parida et al., 2019)
Jatropha curcas shell biodiesel blends	VCR	CCD	CR, blend ratio load	BTE. BSFC, HC, CO, CO_2	(Patel et al., 2018)
Plastic and castor oil biodiesel blend	VCR	BBD	Blend ratio, load, CR	BTE. BSFC, HC, CO, NOx	(Mohamed et al., 2021)

2.6. Application of Artificial Neural Network for ICE

Artificial Neural Networks (ANNs) have become significant instruments in the domain of ICE research, owing to their capacity to model intricate, nonlinear systems without the necessity for explicit physical equations. Conventional analytical models frequently encounter difficulties in accurately representing the highly dynamic interactions among variables such as fuel type, engine load, speed, IT, and air–fuel ratio. ANNs address this challenge by discerning patterns from experimental data, rendering them adept at forecasting essential engine performance metrics such as BTE, BSFC, and torque. Furthermore, they are extensively utilized for predicting engine-out emissions, including NOx, CO, HC, and CO_2, particularly when alternative fuels or additives are incorporated.

In addition to prediction, ANNs are crucial in engine optimization, control, and fault diagnosis. They are frequently combined with optimization methodologies such as GA or PSO to determine optimal fuel mixtures, injection techniques, or operational conditions that achieve a balance between performance and emissions. Within control systems, ANNs assist in regulating vital engine functions such as air–fuel mixture management and ignition timing, while also facilitating the early identification of faults or irregular behaviors based on sensor data. In summary, the utilization of ANNs significantly advances the creation of more efficient, cleaner, and smarter engine systems, thereby reducing dependence on expensive and time-intensive experimental processes.

2.6.1. Artificial Neural Network

The ANN represents the forefront of artificial intelligence. Artificial intelligence encompasses the creation and analysis of intelligence within machines. An intelligent machine functions as a flexible cognitive agent that interprets its surroundings and executes actions aimed at optimizing its chances of achieving a specified objective. Over the last ten years, significant advancements have been made utilizing artificial neural networks. These networks are capable of addressing intricate and non-linear issues, whether they are fully defined or partially defined. Artificial neural networks are extensively utilized across various domains, including engineering, science, and pharmaceuticals. Key areas of application encompass sound and pattern recognition, forecasting market trends, predicting bankruptcy, identifying military targets, and locating mineral exploration sites. Neural networks eliminate the necessity for expensive and impractical physical models, intricate mathematical equations, and elaborate computer simulations. They adeptly manage analog data that may be challenging to process due to the involvement of numerous variables (Bhatt & Shrivastava, 2022).

ANN utilize artificial neurons that mimic the biological neurons found in the human brain to process information. Figure 2.8 illustrates the structure of a biological neuron. In the brain, coded data is transmitted from synapses to the axon through electrochemical substances known as neurotransmitters. This coded information is then relayed to a collection of neurons. These neurons are organized into subsystems, which together form the brain. It is estimated that there are approximately 100 billion interconnected neurons within the human brain (Agwu et al., 2018). The artificial neural network exhibits an intrinsic characteristic similar to that of the human brain in the following ways:

- ✓ Acquiring knowledge through learning from experimental data.
- ✓ Assigning the necessary weights for the purpose of storage.

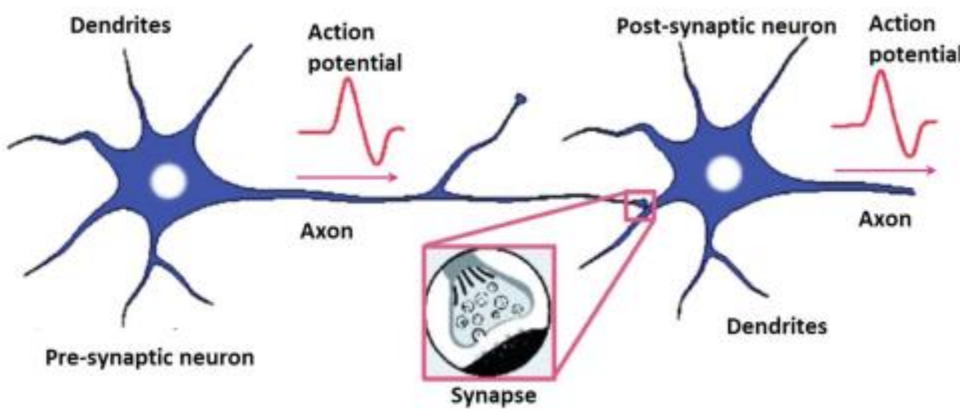


Figure 2.8 Biological neuron (Bhatt & Shrivastava, 2022)

A schematic representation of the ANN model is illustrated in Figure 2.9, which includes an input layer, several hidden layers, an output layer, and a collection of neurons within each layer. Through the process of training, the ANN acquires essential insights regarding the foundational problem by discerning potential non-linear relationships that are embedded within the problem domain. It receives input from external sources, such as experimental data, and establishes connections among them to derive the desired output. The ANN is capable of relearning when new data sets are introduced, adapting its execution accordingly, and forecasting a new set of outputs. In the context of prediction and analysis for engineering challenges, the ANN can serve as an alternative methodology. To facilitate the prediction of multiple output variables, it is designed to handle multiple input variables. This approach differs significantly from traditional methods of comprehending the system without prior information. A well-trained ANN operates more swiftly than conventional techniques in predicting outcomes, as it does not require the resolution of extensive and complex mathematical equations (Banerjee et al., 2018).

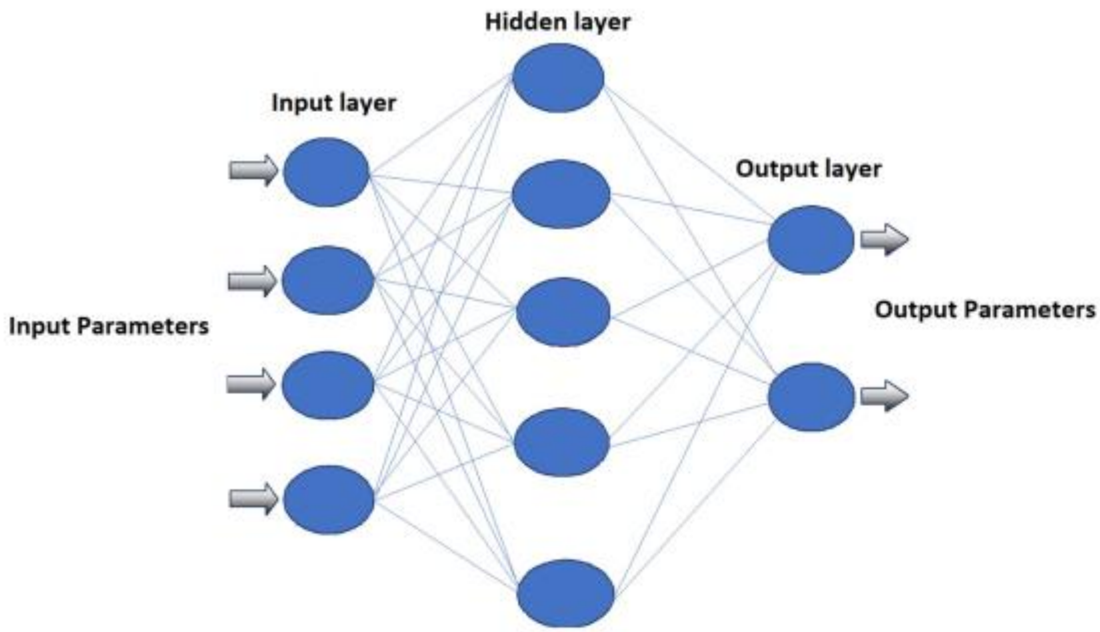


Figure 2.9 ANN schematic diagram

ANN analysis employs a 'black box' methodology to address the issue, thereby relieving the user from the necessity of possessing advanced mathematical knowledge. The neural network retains knowledge and information within the trained framework, which can be readily accessed by the user. ANN offer a high degree of accuracy for previously unobserved data sets related to the base problem, which are not essential during the 'training' phase. However, potential limitations may arise when utilizing the neural network for complex problem-solving. The most significant of these limitations pertains to the data inherent in the base problem, which encompasses a substantial amount of information necessary for training the ANN, potentially distributed unevenly across the system's range. Various algorithms are available for training purposes, including Levenberg–Marquardt, conjugate gradient, and quasi-Newton. The gradient descent algorithm is characterized by a slow learning rate, in contrast to the LM, quasi-Newton, and conjugate gradient algorithms, which are more rapid and employ standard numerical optimization techniques. The intricate nature of ANN may result in increased computation time, energy consumption, and spatial requirements. Recent research has focused on modifying the network topology and design of ANN to achieve enhanced performance (Bhatt & Shrivastava, 2022).

2.6.2. Modeling of CI engine

This section discusses the studies involving ANN modeling related to CI engines. Firstly, it examines standard diesel fuel; secondly, it explores alternative liquid and gaseous fuels; and thirdly, it addresses the comparative modeling and optimization studies.

2.6.2.1. Models with Standard Fuel

The research conducted on CI engines under different operating conditions utilizing standard diesel fuel has been compiled.

(Bietresato et al., 2015) investigated the predictive ability of ANN to evaluate the performance of farm tractors in an indirect manner. The researchers forecasted the BSFC and torque by utilizing indirect indicators such as EGT and the temperature of motor oil from four agricultural tractors. The R^2 values approached 0.996. The researchers concluded that the Gaussian function was preferable to the sigmoidal function. In a comparable investigation (Siami-Irdemoosa, E., & Dindarloo, S. R.,2015), the fuel consumption of the mining truck was forecasted by an ANN utilizing loading time, empty travel time, idle time to load, and payload as input variables. A 6-9-9-1 ANN structure, which included 9 neurons in each of the two hidden layers, was employed, yielding a MAPE of approximately 10 percent.

The temperature of the exhaust valve and the heat transfer coefficient between the valve and its seat were evaluated using two separate ANN models, as reported by (Goudarzi et al.,2015). Two distinct temperatures measured at different locations on the seat, derived from inverse heat problems, were chosen as inputs for the models. A comparison of ten learning algorithms revealed that the LM algorithm exhibited the most favorable convergence characteristics. The model designed to predict the exhaust valve temperature incorporated 15 and 7 neurons across two hidden layers, while the model for the heat transfer coefficient included 10 and 5 neurons, respectively.

In a research investigation focused on a turbocharged diesel engine equipped with a precombustion chamber, the effects of speed, throttle position, and injection pressure on various performance metrics such as BMEP, power, torque, fuel flow, SFC, smoke, CO_2, NOx, and SO_2 were thoroughly examined. An ANN model, utilizing three input variables—namely IP, throttle position, and speed—was employed to predict performance outcomes and emissions independently. The dataset used for testing was utilized to train and validate the model. A single hidden layer comprising between 5 to 15 neurons was implemented for performance parameters, while two hidden layers with neuron combinations of 8-7, 9-5, 9-7, and 10-7 were designated for emission parameters. The back-propagation algorithm, in conjunction with the LOGSIG transfer function, was utilized in the modeling process. Three distinct training functions—Levenberg-Marquardt (LM), Conjugate Gradient with Polak-Ribiere (CGP), and Scaled Conjugate Gradient (SCG)—were assessed, with the authors noting that the LM function exhibited the fastest performance, while the CGP function yielded the highest error rates. The findings indicated that the R^2 and RMSE values were approximately 0.99 and 0.01, respectively, and the MAPE was recorded to be below 8.5. The study strongly advocates for the application of ANN models only in scenarios where experimental results are consistent and stable; otherwise, the use of ANN may not be suitable (Arcaklioğlu, E., & Çelıkten İ, 2017).

(Nikzadfar and Shamekhi, 2022) investigated the individual impact of 10 engine inputs on the soot, NOx, torque, and BSFC of a 1.5 L CI engine to enhance control and calibration processes. The ten distinct engine input parameters include the EGR rate, air pressure and temperature, engine speed, the mass of primary and pilot fuel, exhaust and rail pressure, injection crank angle, and pilot retardation. The authors constructed the engine model utilizing AVL Boost simulation software, incorporating both geometric and phenomenological properties of the engine. The AVL mixing control combustion model was employed for this purpose, which was subsequently validated against experimental test data. The simulated engine model was then used to develop a neural network model. A total of four thousand datasets were generated from this engine model for ANN modeling. Given the nonlinear characteristics of certain output parameters, a two-stage multi-layer perceptron model was implemented. Both models feature two hidden layers; the first model comprises ten neurons in each layer, while the second model consists of ten and eight neurons in each layer, respectively. The outputs of the first model included exhaust temperature, torque, and aspirated air. These outputs served as inputs for the second stage model to predict soot and NOx emissions. The study assessed the individual contributions of these inputs on the outputs through perturbation sensitivity analysis. The authors concluded that the mass of injected fuel had a significant effect on engine emissions and performance parameters.

2.6.2.2. Models with Alternative Fuels

The researchers investigated the application of alternative liquid fuels, such as biodiesel from various sources, alcohols, and others, utilizing ANN models. Some of the authors initially referenced in this study employed MISO models. (Muralidharan et al., 2014) examined and created a model aimed at predicting the emission, performance, and combustion parameters of an engine powered by waste cooking oil biodiesel. They implemented three distinct ANN models that employed back-propagation algorithms to forecast parameters individually. The input parameters taken into account included various load, blend%, CR, and crank angle. The functions TRAINBR, TRAINLM, TRAINCGF, TRAINSCG, TRAINGDX, TRAINGDA, TRAINRP, and TRAINBFG were compared against one another. The findings indicated that the TRAINLM function yielded the shortest convergence time and the lowest MSE value. Upon evaluating the R^2 values for BTE, , IMEP, EGT, BP, SFC and mechanical efficiency, the results were found to be, 0.998, 0.9994, , 0.9995, 0.9972, 0.9982 and 0.9912, respectively.

(Gürgen et al., 2018) investigated the cyclic variability of an engine powered by butanol. They experimentally measured the Coefficient of Variance of IMEP for the engine operating on various fuel mixtures and at different speeds. The collected datasets were utilized to develop an ANN model aimed at predicting cyclic variability while speed and fuel blend input variables. The SCG learning algorithm was employed to train the 2–11-1 ANN network architecture. The R^2 value achieved ranged from 0.737 to 0.9677.

(Arumugam et al., 2022) implemented a 4-2-1 configured ANN model to separately estimate the emission and performance characteristics of a rapeseed biodiesel-fueled engine. The inputs to the ANN included various biodiesel blend%, BSFC, BP, and EGT. The fuel SFC remained relatively consistent across all diesel blends, with the exception of B20, which exhibited a slightly higher reading compared to diesel. The resulting R-value was nearly 1, and the MRE was less than 5%.

(Kshirsagar et al., 2017) conducted a study on the variable IP and IT to assess engine performance utilizing biodiesel. They developed two distinct ANN models; the first employed a 4-16-3 architecture aimed at predicting performance parameters, while the second utilized a 4-14-14-6 architecture to estimate emission characteristics. The inputs for both models included load, IP, IT and fuel blends. The R, NSE, and forecasting uncertainty values were found to be within the ranges of 0.99879–0.99993, 0.990406–0.999802, and 0.011525–0.049462, respectively. These results demonstrate the robustness and high effectiveness of the models developed.

(Ilangkumaran et al., 2016) developed a biodiesel blend of diethyl ether and fish oil. They created a model to predict emission and performance parameters, which included a single hidden layer comprising 20 neurons. The model utilized different load conditions and percentage blends as input variables. The correlation coefficients for BTE and EGT were determined to be 0.997 and 0.999, respectively, while the correlation for exhaust emissions ranged from 0.997 to 1. In a separate investigation, (Sakthivel al., 2023) examined an internal combustion engine powered by fish oil-based biodiesel. The ANN model, configured as 2-20-11, was employed to predict EGT, BTE, CO, NOx, HC, CO_2, and smoke emissions. The network was trained using the backpropagation algorithm with the TRAINLM function. Input parameters included load percentage and types of fuel blends. The mean relative error and correlation coefficient for the predicted outcomes were found to be between 0.02% and 3.97%, and 0.957 to 0.999, respectively.

(Celebiet al., 2021) examined the acoustics and vibrations associated with various biodiesel blends that incorporate natural gas in an unmodified engine. The parameters considered for predicting sound pressure and vibration levels include speed, CN, density and CNG flow rate, which were analyzed separately. The 4-4-1 and 4-5-1 network architectures were employed to explore vibration and sound pressure level (SPL), respectively. Purelin and Logsig transfer functions were utilized in the output and hidden layers, respectively. The results of the model were found to be in close agreement with the experimental data. (Javed et al., 2018) forecasted the noise produced by an engine operating on biodiesel mixed with zinc oxide nanoparticles and hydrogen induction in dual fuel mode. The sound level, measured in decibels, was predicted using a 4–8-1 network, with inputs including load, quantity of nanoparticles, proportion of biodiesel, and proportion of hydrogen, achieving a regression coefficient of 0.99.

In a comparable investigation, (Syed al., 2021) assessed seven learning algorithms in conjunction with three transfer functions to analyze an ANN model created for a hydrogen-diesel dual-fuel mode engine. A comparative matrix was constructed featuring seven training algorithms, namely TRAINLM, TRAINGDX, TRAINGDA, TRAINRP, TRAINBFG, TRAINCGF, and TRAINSCG, alongside three transfer functions: LOGSIG, TANSIG and PURELIN, applied to 16 data sets. The findings of the matrix indicate that the quasi-Newton backpropagation method combined with the TANSIG transfer function outperformed the other algorithms. In another study, (Taghavifar al., 2019) estimated the convective heat transfer coefficient for the engine head, piston walls, and cylinder liner of a hydrogen-fueled diesel engine. This research utilized a CFD based model to generate the necessary data. An ANN model was developed using liquid mass evaporated, equivalence ratio, and temperature as input variables. A 3–17-3 network configuration was chosen, resulting in a RMSE value of 9.13.

2.7. Research gap

Currently, RSM techniques are increasingly utilized to optimize engine performance by adjusting desired outputs and operational parameters. The optimization strategies that emerge from RSM have garnered considerable attention for their applicability in tackling modern engineering issues. Numerous prior studies have thoroughly investigated the effectiveness and precision of RSM techniques in identifying optimal outputs within diverse data sets, particularly focusing on improving the performance and emissions characteristics of CI engines. Numerous studies have been conducted regarding the application of n-butanol in CI engines, focusing on its impact on engine performance and exhaust emissions. Despite this, there remains a lack of research exploring the potential of artificial intelligence and statistical methodologies, specifically ANN and RSM, to predict and optimize the input-response variables associated with n-butanol-diesel blends in CI engines. To address this research gap, a study was undertaken to develop an appropriate ANN model aimed at accurately forecasting the performance and emissions of n-butanol-diesel blends, thereby facilitating the identification of optimal operating conditions for CI engines. Furthermore, an RSM-based approach was employed to identify the most effective working parameters for these fuel blends.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Introduction

This chapter presents the experimental design, fuel preparation, analytical techniques employed to evaluate and optimize the emission and performance characteristics of a CI engine fueled with diesel-n-butanol blends. Given the increasing demand for cleaner combustion alternatives, the integration of oxygenated fuels like n-butanol with conventional diesel offers a promising route to enhance engine efficiency while minimizing harmful emissions. However, the complex interactions between fuel properties, engine operating conditions, and emission behavior necessitate robust optimization approaches.

To effectively capture and interpret these interactions, this study employed two advanced modeling and optimization techniques: RSM and ANN. RSM, a statistical tool, is used to develop empirical models and analyze the effects of multiple input variables on performance metrics, while ANN provides a data-driven approach capable of modeling nonlinear and dynamic engine behavior with high accuracy. This chapter details the experimental setup, blend ratios, variables considered, and modeling procedures for both RSM and ANN, laying the groundwork for performance prediction and optimization. Additionally, this chapter presents the materials and equipment utilized in the study and offers a clear overview of the sequential procedures followed throughout the experiment. The tasks performed at each phase are summarized in the flowchart shown in Figure 3.1.

3.2. Materials

The careful selection and understanding of materials and equipment are fundamental to the success of any experimental research. These components serve as the foundation for obtaining accurate and reliable data, which are critical for subsequent modeling, analysis, and optimization. Before commencing the experimental work, it is essential to thoroughly examine the characteristics of each material and instrument such as their functional principles, measurement ranges, precision, and limitations: to ensure their suitability for the study.

In this investigation, various chemicals including diesel fuel and n-butanol, as well as laboratory tools like beakers, measuring cylinders, and an ultrasonicator for fuel blending, were used. The experimental work also involved the TMBC 8 single-cylinder CI engine, whose specifications are detailed in Table 3.1. A comprehensive list of all materials, equipment, and their relevant specifications is provided in Table 3.2. For the purpose numerical modeling and statistical analysis, Minitab software was used to implement RSM, while MATLAB was employed for developing and training ANN models. These software tools enabled efficient data processing, regression analysis, prediction, and performance optimization.

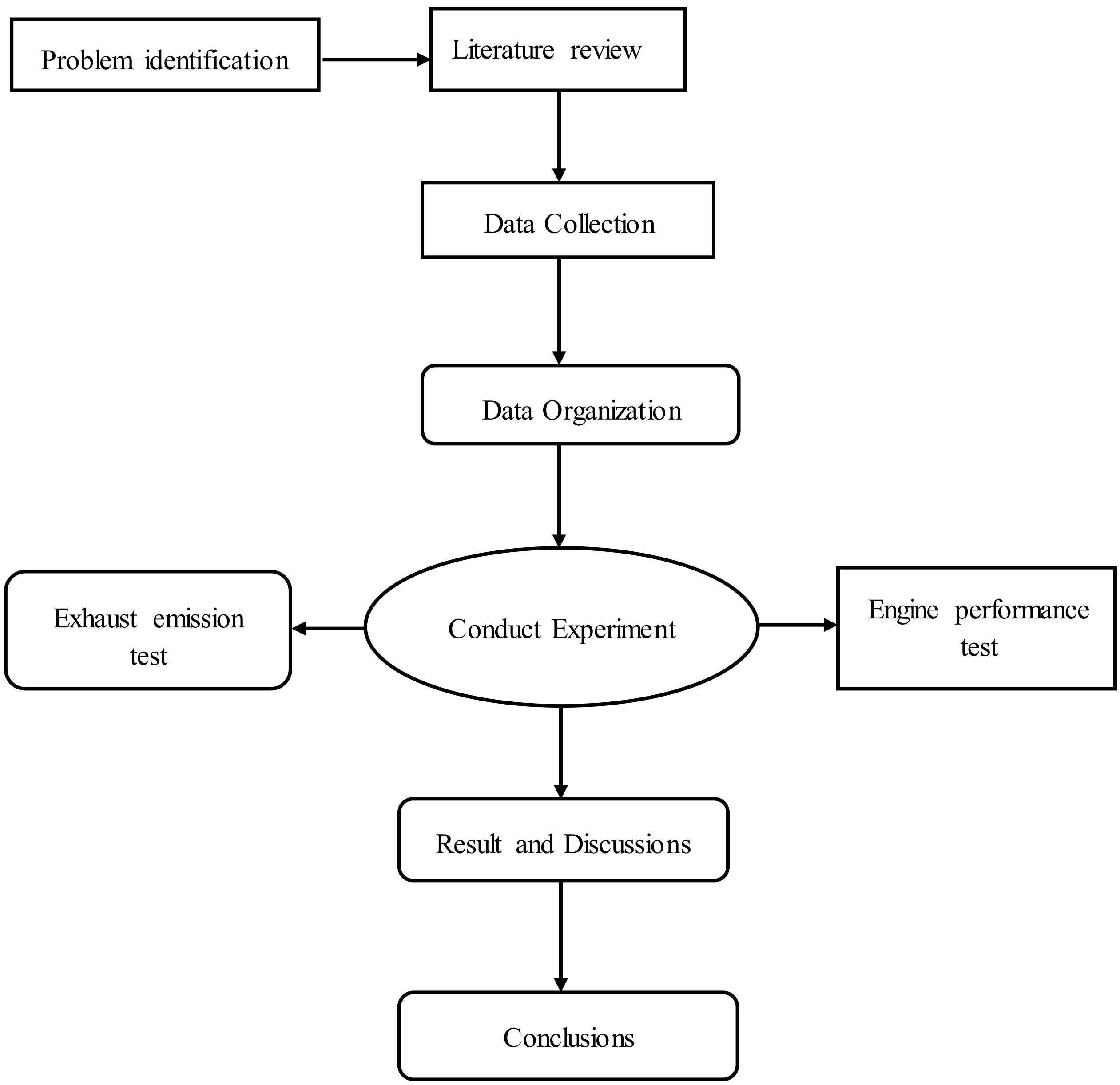


Figure 3.1 Flowchart of methodology

Table 3.1 Specifications of TMBC 8 diesel engine

Type of engine	Compression ignition
Fuel	Diesel
No. of cylinders	1
No. of strokes	4
Type of air intake	Naturally aspirated
Type of cooling	Water-cooled
Compression ratio	24:1
Output power (kW)	5.1 kW@3000 rpm
Cylinder bore	77 mm
Stroke	70 mm

Table 3.2 Materials and equipment required for this study

No	Item
1	n-butanol
2	Diesel fuel
3	Engine test rig
4	Exhaust gas analyzer
5	Data acquisition system
6	Ultrasonicator cleaner
7	Beakers
8	Conical flasks
9	Measuring cylinder
10	Minitab software
11	MATLAB software

3.3. Methods

This research was carried out utilizing the subsequent methodologies, which include both experimental and computational approaches. The experiment data developed predictive models using RSM and ANN, aiming to optimize the performance and emission characteristics of a diesel engine operating with diesel-n-butanol blend. RSM applied to design and analyze the experimental trials efficiently, while ANN used to model complex nonlinear relationship between input variables and engine responses. Comparative evaluation between RSM and ANN models performed to determine the more accurate and reliable prediction technique.

3.3.1. Preparing blend of fuel samples

The preparation of diesel-n-butanol blends undertaken by formulating fuel samples designated as B10 (comprising of 10% n-butanol and 90% diesel), B20 (containing 20% n-butanol and 80% diesel), and B30 (featuring 30% n-butanol and 70% diesel) by volume. The n-butanol used in study was analytical grade (99% purity) to ensure fuel consistency and prevent contamination that could affect combustion behavior or engine performance. Table 3.3 detailed the physicochemical properties of diesel-n-butanol blends. Diesel fuel sourced from certified supplier to maintain uniformity throughout the experimental campaign.

To achieve a homogeneous and stable mixture, the blending process utilized an ultrasonicator cleaner, which provides superior dispersion compared to conventional mixing techniques such as hand shaking. Ultrasonication aids in breaking down any phase boundaries between the diesel and n-butanol molecules, resulting in a uniform and thermodynamically stable blend. This process also minimizes the chance of phase separation. The blended fuels prepared airtight bottle containers and stored in a cold, dark environment to prevent evaporation or degradation of n-butanol due to exposure to light or temperature fluctuations. Prior to engine testing, each blend visually inspected to ensure that no phase separation or precipitation has occurred. Additionally, safety precautions followed during the blending process, including the use of gloves and fume hoods, due the flammability and volatility of n-butanol. Figure 3.2 below illustrates the process of blending diesel-n-butanol fuel using an ultrasonicator.

Figure 3.2 Photograph of the ultrasonicator used for mixing the fuel blends

Table 3.3 Physicochemical properties of diesel-n-butanol blends

Property	Diesel (B0)	B10	B20	B30
Viscosity at 40°C (mm^2/s)	2.60	2.40	2.20	2.0
Density (kg/m^3)	830	826	820	815
Lower heating value (MJ/kg)	42.5	40.8	39.1	37.4
Flash point (°C)	65	52	40	30
Cetane number	50	47	44	41
Latent heat of vaporization (kJ/kg)	250	330	410	490
Oxygen content (% wt)	0	2.1	4.2	6.3

3.3.2 Designing experimental matrix using response surface methodology (RSM)

RSM is a power collection of mathematical and statistical techniques used to model, analyze, and optimize processes influenced by multiple interacting variables. Its primary objective is to develop predictive models and identify optimal conditions that maximize or minimize the desired response variables. In the context of this study, RSM was implemented to investigate the effects of key operating parameters on both engine performance and emission characteristics in a CI engine running on diesel-butanol blends. The CCD, a widely used design structure under RSM, was employed to systematically plan the experimental trails. This design allows for the development of 2nd order polynomial models that capture both linear and interaction effects of the independent variables. In this study two independent factors were considered critical: engine load and n-butanol blending ratio. These parameters were selected due to their significant influence on combustion behavior, thermal efficiency, and pollutant formation.

The experimental matrix was generated using Minitab software, which also facilitated the ANOVA to determine the statistical significance and adequacy of the developed models. ANOVA helps identifying the contribution of each factor and their interactions on the response variables such as BT, BP, BSFC, CO, CO_2, HC and NOx emissions. RSM enabled efficient exploration of the design space, reducing the number of experiments required while ensuring high-quality, reliable results. By analyzing the response surfaces and contour plots, optimal parameter combinations can be visually interpreted. Moreover, the predictive models derived from RSM help to anticipate engine behavior under untested conditions, making it a valuable tool for both experimental planning and practical implementation.

Table 3.4 presents the selected range and levels of the input variables, while Figure 3.3 outlines the methodological workflow applied in the RSM analysis. Equation 3.1 represents the general form of the 2nd order polynomial model used to fit the experimental data and predicted engine responses under various conditions. Through this approach, RSM not only supports the goal of enhancing engine performance and reducing emissions but also contributes to reducing experimental effort, time, and cost while maintaining a high degree of accuracy in optimization outcomes.

$$Y = X_0 + \sum_{i=1}^{k} X_i A_i + \sum_{i=1}^{k} X_{ii} B^2 i + \sum_{j=i+1}^{k} . \sum_{i=1}^{k} X_{ij} C_{ij} \tag{3.1}$$

Where Y is response; A_i, B_i, and C_i are the input variables; X_0 and X_i represent intercept and first-order regression coefficient, respectively; k is the total number of experiments and X_{ii} is the quadratic regression coefficient.

Table 3.4 Range of process variables used in CCD

Input variables	Coded	High	Average	Low
Engine load (%)	X_1	75	50	25
n-butanol ratio (%)	X_2	10	20	30

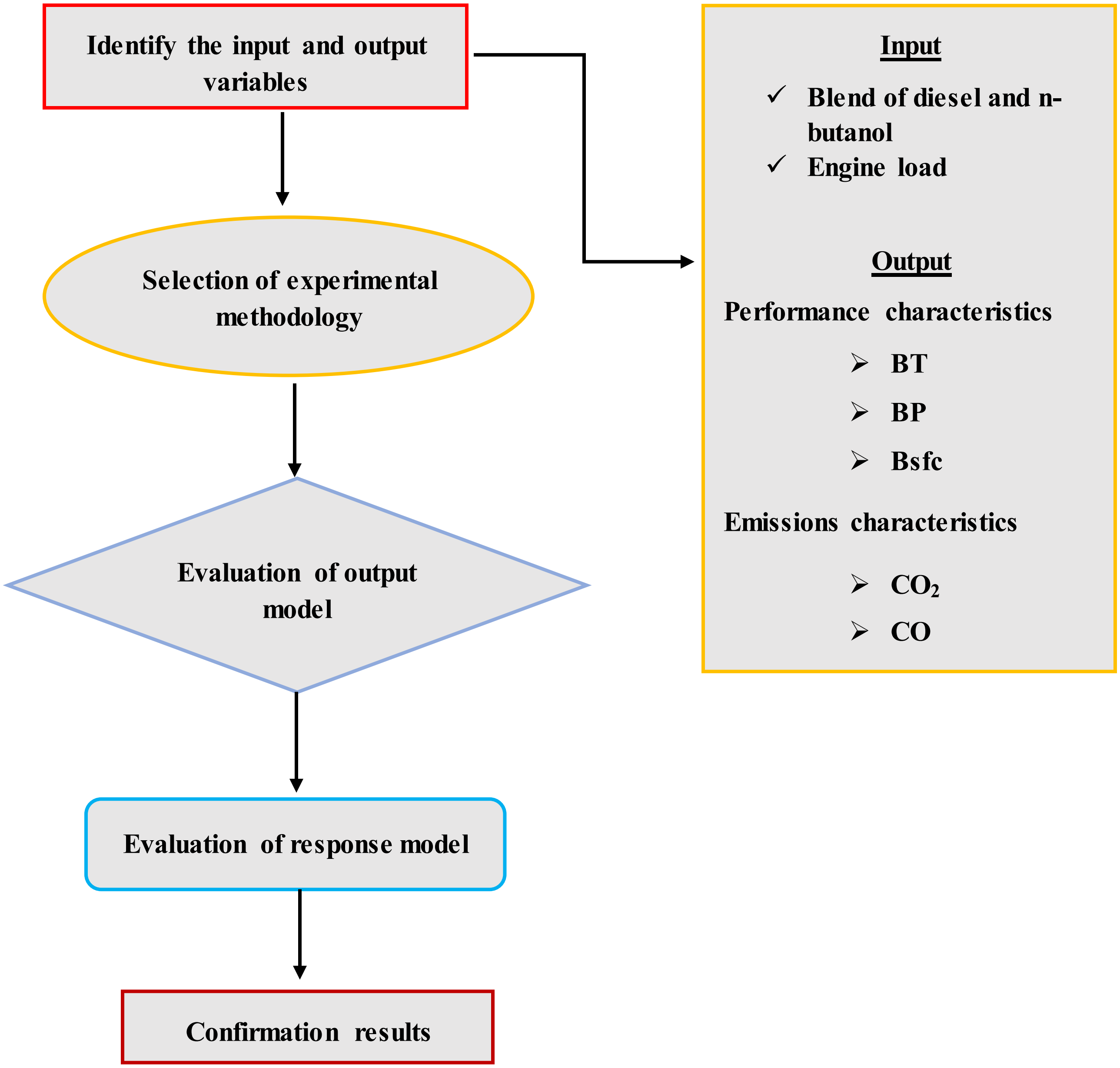


Figure 3.3 Flowchart of RSM

3.3.3. Artificial neural network for modeling CI engine

An essential feature of machine learning systems, artificial neural networks (ANNs) are especially useful for modeling intricate, nonlinear interactions between variables in scientific and engineering applications. ANN is made up of layers of interconnected processing units called neurons that interact through weighted synapses, drawing inspiration from the biological structure of the human brain. During training, these weights are modified to identify patterns in the data, allowing for precise forecasts and decision-making.

In the present study, a predictive model for assessing the engine performance and emission characteristics of a CI engine powered by diesel-n-butanol blends was developed using ANN. Due to their substantial impact on the combustion process, the two input variables: engine load and n-butanol ratio were chosen. Thirteen experimental observations from RSM-designed trials made up the dataset used to train and test the ANN model. MATLAB R2020a was used to implement the feed-forward backpropagation ANN network design. An input layer with two neurons, a single hidden layer with ten neurons, and an output layer generating responses like BT, BP, BSFC, CO, CO_2, HC, and NOx emissions made up the network structure. The Leverberg-Marquart (TRAINLM) optimization technique, which is renowned for its quick convergence and precision in approximating nonlinear functions, was used in the training procedure. During backpropagation, weights were updated using the LEARNGDM adaptation learning function. To capture nonlinearity in the data, a TANSIG transfer function was used in both the hidden and output layers. MSE was used as the main indicator to assess the model's performance, guaranteeing that there was little difference between the expected and actual results.

The data was standardized before training to increase the model's accuracy, and cross-validation was used to avoid overfitting. The trained ANN model showed promise as a reliable tool for forecasting engine performance under various operating situations by successfully capturing the complex interactions between input factors and output responses. The ANN architecture configuration employed in this investigation is shown in Figure 3.4, which highlights the information flow from input parameters to expected performance and emission outcomes.

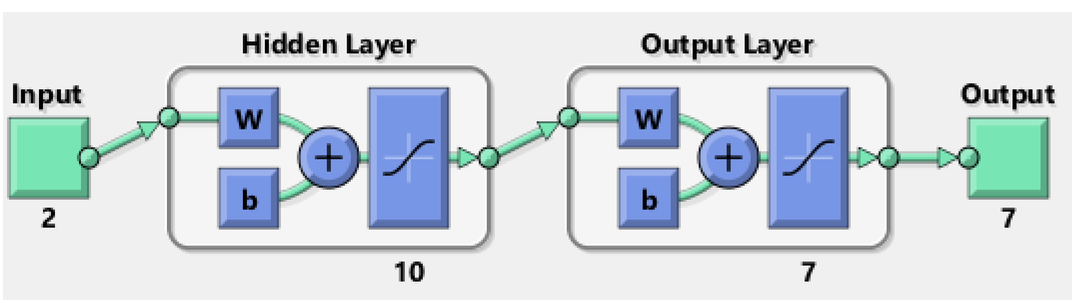


Figure 3.4 ANN structure for predicting performance and emission outcomes

3.3.4. Comparison parameters of RSM and ANN

The findings from the RSM and ANN were compared to the real experimental data related to engine performance and emission parameters in order to evaluate the predicting abilities of the created models. The purpose of this comparison study was to assess each modeling approach's precision, resilience, and capacity for generalization. The degree of agreement between the experimental and anticipated values was measured using a number of statistical performance metrics. These consist of the RMSE, MSE, and R^2. Each of these metrics offers unique insights: RMSE provides a more comprehensible error to measure in the same units as the original data, MSE shows the average squared difference between predicted and actual values, and R^2 quantifies the percentage of variance in the experimental data that is explained by the model.

An impartial and thorough assessment of both modeling frameworks is made possible by the application of these error functions. Better model performance is indicated by higher R^2 and lower MSE/RMSE values. These measurements are essential for determining the best method for predicting engine performance under different operating situations as well as for verifying the accuracy and dependability of the prediction models. Equations 3.2–3.4 provide the mathematical formulations for these evaluation parameters, which were applied uniformly to all performance and emission outputs, including BT, BP, BSFC, and emissions of CO, CO_2, HC, and NOx. The purpose of this comparison is to illustrate the advantages and disadvantages of each modeling method. ANN gives greater flexibility and the capacity to simulate complex nonlinear interactions, whereas RSM offers ease of interpretation and adaptability for experimental design. Future researchers and engineers can choose the best tool for engine modeling and optimization tasks with the aid of this dual evaluation.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}\left(Y_e - Y_{pi}\right)^2}{\sum_{i=1}^{n}(Y_{ei} - Y_{av})^2}\right) \tag{3.2}$$

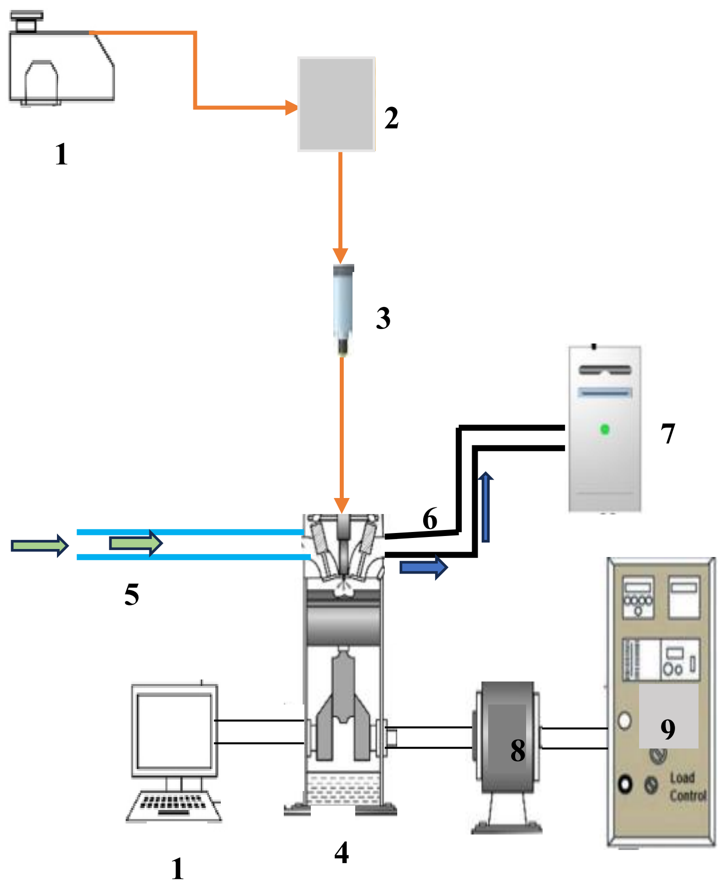
$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{ei} - Y_{pi}\right)^2 \tag{3.3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i==1}^{n}\left(Y_{ei} - Y_{pi}\right)^2} \tag{3.4}$$

Where n is the total number of experiments and $Y_p$and Y_e; the predicted and observed values, respectively, Y_{av} is an average value and $\overline{Y}_p$ is mean of predicted value.

3.4. Experimental analysis

A TMBC 8 diesel engine from Addis Ababa Science and Technology University's Department of Mechanical Engineering's automotive laboratory was used for the experimental study. The engine is a single-cylinder, water-cooled, naturally aspirated, four-stroke engine with a maximum output torque of 5.1 kW at 3000 rpm. Figure 3.5 shows a schematic of the experimental setup. The purpose of this study was to examine the diesel engine's performance and emission characteristics under different load scenarios when it was powered by blends of diesel and butanol. To assess how various blending ratios, affect engine behavior, key performance parameters like BT, BP, and BSFC were monitored. To ensure data reliability, the engine was first allowed to reach a steady-state prior measurement were taken, and each point was repeated three times to reduce experimental variability.



1 Fuel tank
2 Fuel filter
3 Fuel pump
4 Test engine
5 Air intake
6 Exhaust manifold
7 Exhaust emissions analyzer
8 Dynamometer
9 Control panel
10 Data acquisition system

Figure 3.5 Schematic layout of experimental setup

A KANE-EGA exhaust gas analyzer, which provides real-time measurements of such significant pollutants as CO, CO_2, HC, and NOx, was used for emission analysis. This made it possible to thoroughly assess how different diesel-n-butanol combinations affected the environment and how fuel parameters affected combustion. utilizing RSM and ANN techniques, prediction models were created utilizing the test findings produced by this experimental process. The identification of operating parameters for improving engine performance while reducing hazardous emissions was made possible thanks in large part to these models. Table 3.5 displays the experimental matrix that describes the test setup.

Furthermore, as shown in Table 3.6, the experiment was carried out using a Central Composite Design (CCD) matrix, which included 13 experimental runs. To capture the effects of varying operating conditions, important engine performance and emission metrics were methodically assessed during these trials.

Table 3.5 Configuration matrix for experimental evaluation

Engine condition	Fuel used for reference	Fuel for experiment	Parameters
Speed (2400 rpm) Load (25%, 50% and 75%) Compression ratio (24:1)	Diesel	B10 B20 B30 For optimization	Engine performance o BP o BT o BSFC Exhaust emissions o CO o CO_2 o NOx o HC

Table 3.6 Experimental matrix created using central composite design

StdOrder	Run	Engine load	n-butanol ratio
1	1	25	10
4	2	75	30
5	3	15	20
13	4	25	20
11	5	50	20
9	6	50	20
6	7	80	20
7	8	50	0
12	9	50	20
3	10	25	30
10	11	50	10
8	12	50	30
2	13	5	10

3.4.1. Performance parameter analysis

The performance parameters of a single-cylinder CI engine running on pure diesel and diesel-n-butanol blends under various engine load scenarios are extensively studied in this article. BP, BT, and BSFC are the three main engine performance indicators that are the subject of the analysis. These measurements are crucial for assessing the engine's fuel economy, mechanical efficiency, and blended fuel adaptability. The engine's performance was optimized by using experimental data as input for RSM and ANN-based modeling.

3.4.1.1. Brake power (BP)

The useful power output at the engine's crankshaft is represented by brake power, which is expressed in kilowatts (kW). Because it precisely reflects the engine's ability to provide mechanical energy for work, it is an essential performance metric. Torque and angular speed are used to calculate BP, which is impacted by fuel characteristics and combustion quality. In this investigation, both pure diesel and diesel-n-butanol blends showed differences in brake power under various engine load conditions. Due to its oxygenated nature, which can improve combustion completeness and impact power output, the integration of n-butanol is anticipated to have an impact on combustion efficiency. Accurate BP measurements were made possible by the computerized test bench's real-time torque and load monitoring. These measurements were then examined using RSM and ANN models to determine the circumstances that optimize output efficiency.

3.4.1.2. Brake torque (BT)

The force torque produced by the engine and sent to the dynamometer is known as brake torque, and it is measured in Nm. It is a clear indicator of the engine's capacity to carry out rotating action. When evaluating the engine's performance, torque is crucial, particularly when dynamic loading is present. In order to assess the impact of adding n-butanol on torque delivery, BT was measured at different load levels in this experimental investigation. The torque characteristics can be changed by n-butanol's lower heating value and oxygen concentration, which can affect flame speed and combustion pressure.

3.4.1.3. Brake specific fuel consumption (BSFC)

BSFC is a key metric that measures fuel efficiency in ICEs. It is commonly stated in g/kWh. It shows how much fuel is needed to produce one kilowatt of BP in an hour. BSFC calculates by dividing the fuel's mass flow rate by the BP output. Because engines typically run more effectively at greater loads due to improved combustion stability and lower relative frictional losses, BSFC generally falls with increasing load. The efficiency of diesel-n-butanol blends in comparison to conventional diesel fuel was assessed in this study using BSFC. Higher fuel consumption may be necessary to produce equal power due to n-butanol's lower energy content; however, its oxygenation may encourage cleaner combustion and improved fuel-air mixing, which can counteract some efficiency losses. The creation of RSM and ANN models to forecast fuel efficiency and determine the best blend and load combinations for reduced fuel consumption and emissions relied heavily on the gathered BSFC data.

3.4.2. Emission analysis

To assess their environmental impact, the emission characteristics of CI engines powered by mixtures of diesel and n-butanol were carefully examined under various load scenarios. A KANE-EGA gas analyzer was used to measure emissions in real time. CO, CO2, HC, and NOx are the main exhaust pollutants evaluated in this study. The findings were crucial inputs for creating predictive models that optimized engine operating parameters for low emissions using RSM and ANN.

3.4.2.1. Carbon monoxide (CO)

The primary cause of carbon monoxide, a poisonous, colorless, and odorless gas, is incomplete combustion of hydrocarbon fuel. Zones where the fuel-air mixture is excessively rich, which leaves insufficient oxygen to completely burn carbon into CO2, are where CO emissions in CI engines are most common. Although CO generation is typically more closely linked to mixes, it can also happen in extremely lean situations because low flame temperatures prevent full oxidation.

3.4.2.2. Carbon dioxide (CO_2)

One of the main byproducts of combustion is carbon dioxide, which can be used to gauge how well fuel has been oxidized. It is created when the hydrocarbon fuel's carbon content completely combines with oxygen during burning. Since more fuel's carbon is being converted to its fully oxidized state rather than creating partial combustion products like CO or HC, a rise in CO2 emissions usually indicates efficient combustion.

3.4.2.3. Hydrocarbons (HC)

Unburned or partially burnt fuel molecules that exit the combustion chamber are the source of hydrocarbon emissions. They may result from fuel-rich areas, cracks that prevent flames from spreading, or flame quenching close to cylinder walls. Fuel volatility, evaporative behavior, and ignition delay can all affect HC emissions in engines running on oxygenated fuels. Higher loads typically result in more complete combustion, which lowers HC emissions. However, at some blend ratios, inadequate atomization or incorrect air-fuel mixing may result in localized rich zones, which would increase the creation of HC. Moreover, mechanical wear such cylinder wall deposits and piston ring blow-by may increase HC emissions, particularly during prolonged engine use..

3.4.2.4. Nitrogen oxides (NOx)

At high combustion temperatures, atmospheric nitrogen reacts with oxygen to generate nitrogen oxides (NOx), which are mainly nitric oxide (NO) and nitrogen dioxide (NO2). The temperature inside the cylinder, the availability of oxygen, and the timing of ignition all have a significant impact on the production of NOx. Because of their high compression ratios and peak combustion temperatures, CI engines are especially vulnerable to significant NOx emissions.

3.5. Experimental procedures

The trial process started with a warm-up phase utilizing pure diesel fuel to guarantee steady and dependable engine functioning throughout the tests. To achieve a steady operating temperature, the engine was run at idle speed with no load for about fifteen minutes. In order to reduce the impact of cold-start effects and guarantee that future performance and emission measurements were carried out under steady-state thermal conditions, this warm-up phase is crucial. Following stabilization, three distinct load levels 25%, 50%, and 75% of the engine's rated capacity were used to test the engine's performance under various operational demands. In order to separate the effects of load and fuel composition, the baseline measurements were initially taken using standard diesel fuel at a constant engine speed of 2400 rpm, which was maintained throughout all test situations. Diesel-n-butanol fuel blends B10, B20, and B30 were gradually substituted by regular diesel after the baseline testing.

An integrated dynamometer and automated data acquisition system were used to measure performance metrics like BT, BP, and BSFC for each test condition. A calibrated fuel burette was used to precisely monitor fuel consumption rates and measure the amount of fuel used in each test cycle. An sophisticated KANE-EGA exhaust gas analyzer was used to measure the environmental impact of the various fuel blends. Real-time data on important emission species, such as CO, CO2, HC, and NOx, were provided by this instrument. To evaluate how n-butanol affects the combustion process and pollution, these emissions were measured for each fuel blend at all load levels.

Additionally, the experiments were conducted utilizing a systematically developed experimental matrix through RSM to support the modeling and optimization part of the project. In order to reduce the number of experimental results that were subsequently used to train and validate ANN models, the matrix guaranteed an effective and statistically balanced combination of independent variables (blend ratio and load). This allowed for precise prediction and optimization of performance and emission characteristics under a variety of engine conditions.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

The collected data from this research underwent comprehensive analysis, leading to an in-depth discussion of key findings and significant trends. The study placed strong emphasis on several crucial areas:

- **Combustion Emission characteristics:** A detailed emission analysis of the CI engine was conducted to evaluate the environmental impact of various fuel blends and operating conditions, focusing on pollutants such as NOx, CO, CO_2, and HC.
- **Engine performance evaluation:** The performance characteristics of the CI engine were assessed under different loads, considering metrics such as BT, BP, and BSFC.
- **Optimization through RSM**: RSM was utilized to methodically explore the interactive influences of critical factors on engine performance. This approach facilitated the determination of ideal operating conditions that optimize both performance and emissions.
- **Predictive modeling using ANN:** An ANN was created to accurately forecast engine performance and emission outputs.

4.1. Emission analysis of CI engine

This section provides the results of emissions derived from the test bench of the CI engine, presented through graphical representations. The main emissions assessed include CO_2, CO, HC, and NOx. These emissions were scrutinized under various operating conditions to enhance understanding of the combustion characteristics and the environmental implications of the engine. Particular emphasis was placed on how varying fuel compositions and engine loads affected each type of pollutant.

4.1.1. Carbon dioxide emission

Figure 4.1 depicts the fluctuations in CO_2 emissions associated with various test fuels under different engine loads. A noticeable upward trend in CO_2 emissions corresponding to increased load is apparent, which corresponds with the understanding that higher engine loads necessitate greater fuel consumption, resulting in more vigorous combustion processes. Among the fuels evaluated, pure diesel (B0) consistently demonstrated the highest levels of CO_2 emissions in comparison to the n-butanol/diesel blends (B10, B20, and B30). In quantitative terms, B0 generated CO_2 emissions that were approximately 2.60%, 4.60%, and 7.73% higher than those produced by B10, B20, and B30, respectively. This observation indicates a decrease in CO_{22} production as the n-butanol content in the blend increases.

The comparatively lower CO_2 emissions observed in the blended fuels can be ascribed to the oxygen-rich characteristics of n-butanol, which enhances cleaner combustion by improving the oxidation of the fuel mixture. Nevertheless, because n-butanol possesses a lower carbon content than diesel, the total carbon available for oxidation is diminished, resulting in a slight reduction in CO_2 generation. It is crucial to recognize that a higher concentration of CO_2 in exhaust emissions generally indicates more complete combustion, as carbon atoms are fully oxidized. This implies that the increased CO_2 levels observed in B0 are a result of a more carbon-dense fuel undergoing effective combustion. Such results are frequently supported by optimal in-cylinder conditions (adequate temperatures, sufficient oxygen availability, and efficient air-fuel mixing) that enhance the conversion of CO-to- CO_2 during the combustion process.

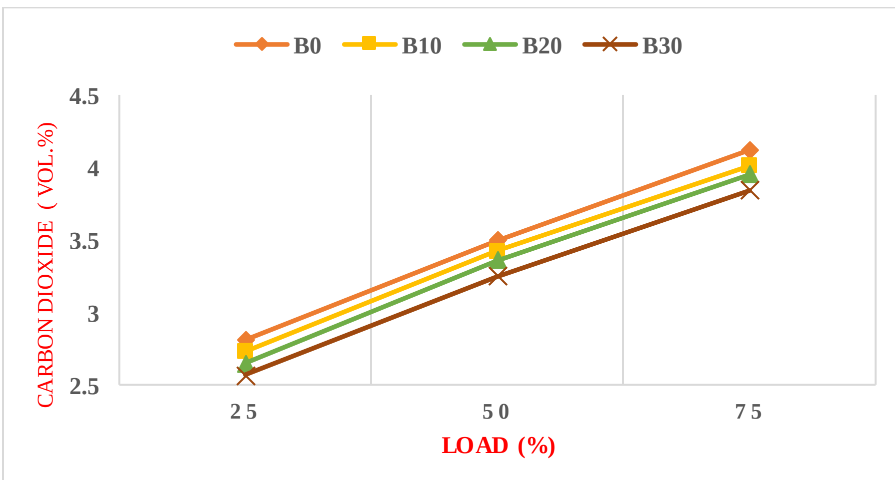


Figure 4.1 Effect of engine load on carbon dioxide emission

4.1.2. Nitrogen Oxides emission

Nitrogen Oxides (NOx) are predominantly generated due to elevated combustion temperatures within the engine cylinder, where nitrogen and oxygen from the intake air engage in thermal reactions. Figure 4.2 illustrates the fluctuation in NOx emissions across various engine loads for the different test fuel blends. The data indicates that pure diesel (B0) consistently produced the highest NOx emissions under all load scenarios. Specifically, the NOx emissions from B0 were approximately 6.96%, 11.84%, and 14.90% greater than those recorded for the B10, B20, and B30 blends, respectively. In contrast, the B30 blend demonstrated the most significant decrease in NOx emissions, establishing it as the most effective fuel among those tested in reducing NOx formation.

The decrease in NOx emissions with an increase in n-butanol content can be linked to several inherent characteristics of the oxygenated fuel. A key factor is the high LHV of n-butanol, which absorbs considerable heat during the vaporization process, resulting in a cooling effect within the combustion chamber. This cooling effect reduces the peak flame temperature, thus diminishing the conditions that are conducive to NOx production. Furthermore, the oxygen-rich molecular structure of n-butanol improves combustion efficiency while simultaneously mitigating local hotspots that lead to thermal NOx formation. This dual effect—facilitating complete combustion while lowering peak temperatures—significantly contributes to the reduction of NOx emissions. The interplay of decreased flame temperature and enhanced oxygen distribution within the cylinder elucidates the superior NOx reduction capabilities of higher n-butanol blends, particularly B30.

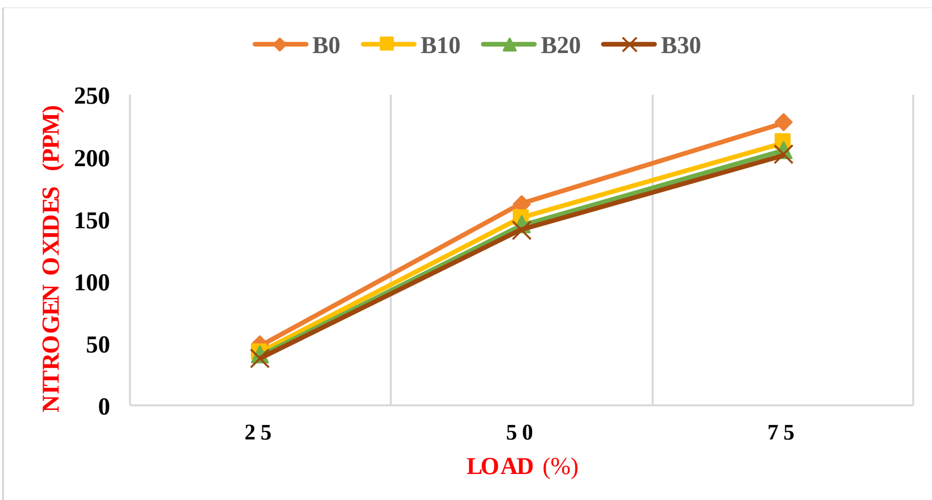


Figure 4.2 Effect of engine load on nitrogen oxides emission

4.1.3. Carbon monoxide emission

Elevated carbon monoxide emissions frequently arise from the incomplete combustion of fuels, a phenomenon that transpires when essential combustion conditions are not satisfied. To achieve complete oxidation, four vital factors need to be optimized: (1) an adequate supply of oxygen, (2) effective mixing of air and fuel, (3) sufficient reaction time, and (4) a high concentration of oxygen within the combustion chamber. Should any of these conditions be deficient, partial oxidation of carbon-based compounds will take place, resulting in heightened CO production.

The influence of fuel composition on CO emissions is clearly illustrated in Figure 4.3, which presents a comparison of various fuel blends under different engine load conditions. It is particularly noteworthy that the B30 blend resulted in the highest levels of CO emissions across all tested load scenarios. This phenomenon can be explained by the characteristics of n-butanol; its elevated latent heat of vaporization serves to cool the combustion process, while its low cetane number contributes to a delay in ignition. Collectively, these attributes lead to a decrease in combustion efficiency, thereby facilitating incomplete oxidation and resulting in increased CO emissions. Conversely, the butanol-free blend (BO) exhibited markedly lower CO emissions, with reductions of approximately 4.56%, 9.13%, and 16.19% when compared to B10, B20, and B30, respectively. This observed inverse relationship between the concentration of n-butanol and combustion efficiency indicates that higher levels of alcohol in the fuel exacerbate the issue of incomplete combustion.

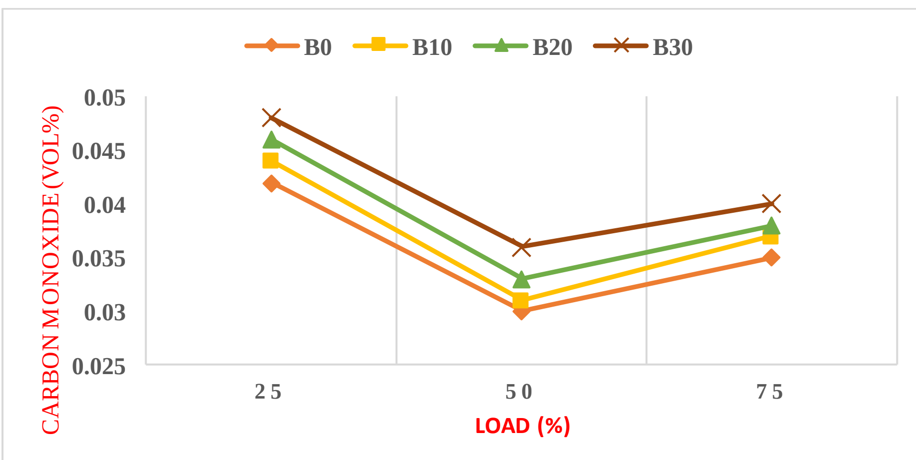


Figure 4.3 Effect of engine load on carbon dioxide emission

4.1.4. Hydrocarbon emission

Hydrocarbon emissions mainly arise from fuel that is either unburned or only partially combusted, which escapes the combustion process as a result of inefficiencies within the engine cylinder. Various factors play a role in this occurrence, such as inadequate air-fuel mixing, flame quenching occurring near the cooler walls of the cylinder, and a lack of sufficient time for complete combustion.

Figure 4.4 depicts the correlation between HC emissions and engine load across various fuel blends. A clear trend is observed: HC levels decrease initially as the load increases, reaching an optimal level before escalating again at higher loads. This trend is consistent for both pure diesel (B0) and n-butanol blends (B10–B30). The initial decrease is attributed to the fact that moderate loads improve combustion efficiency—higher cylinder temperatures and better air-fuel mixing facilitate more thorough fuel oxidation. However, at extreme loads, an overabundance of fuel injection may result in localized oxygen deficiency and incomplete combustion, causing HC emissions to rise. Significantly, B0 surpassed all blended fuels in reducing HC emissions, achieving reductions of 7.33%, 11.42%, and 19.14% when compared to B10, B20, and B30, respectively. The subpar performance of n-butanol blends can be attributed to two primary characteristics:

- ✓ Elevated latent heat of vaporization, which results in cooling of the combustion chamber and hinders the preparation of the fuel-air mixture.
- ✓ Low cetane number, which extends the ignition delay, thereby providing insufficient time for complete combustion prior to the exhaust cycle.

Adding more n-butanol to the fuel blend could have a detrimental effect on combustion efficiency, particularly when there is a high load.

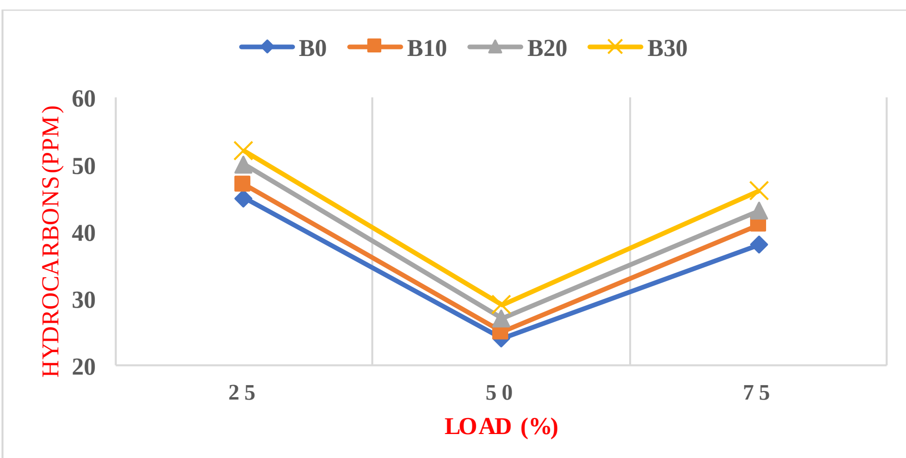


Figure 4.4 Effect of engine load on hydrocarbons emission

4 .2. Engine performance analysis under varying load conditions

This section evaluates how engine load affects key performance indicators like BT, BP, and BSFC. These metrics serve as crucial markers of an engine's fuel economy and operational effectiveness under a range of operating circumstances.

4.2.1. Brake torque

Rotational force, which is crucial for comprehending an engine's pulling capacity and responsiveness, is measured by brake torque (BT). BT performance for different gasoline mixes under varied engine loads, measured at a constant speed of 2400 rpm, is shown in Figure 4.5. The following patterns offer important new information about how fuel mix affects engine performance:

- **Load-dependent torque behavior:** Since improved fuel delivery satisfies the increased power requirements, all tested fuels showed the expected steady rise in BT as engine load increased. At 75% load, the pure diesel (B0) produced a maximum torque of 6.75 Nm.
- **Fuel blend performance gradient:** The torque reduction pattern of the n-butanol blends was consistent: B10 is typically 1.26% less than B0, B20 is often 3.15% less than B0, and B30 is typically 4.62% less than B0.

The reduction in torque observed with alcohol-blended fuels can be attributed to two main factors:

1. Lower energy content: n-butanol releases less energy per unit volume during burning than conventional diesel due to its lower calorific value, which results in a lower torque output.
2. Altered combustion characteristics: n-butanol cools the intake charge and may impede the combustion process because of its higher latent heat of vaporization. Its lower cetane number also causes a longer ignition delay, which can lower torque generation and have a negative impact on combustion efficiency.

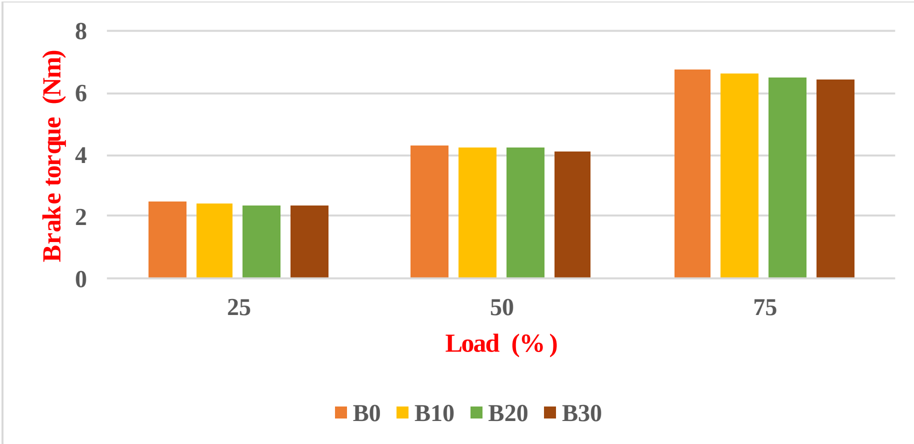


Figure 4.5 Effect of engine load on brake torque

4.2.2. Brake power

Brake power (BP) reflects the engine's usable output power delivered to the crankshaft, directly influenced by combustion efficiency and load demand. Figure 4.6 illustrates the characteristics of brake power (BP) for the evaluated fuel blends under various engine loads, recorded at a steady speed of 2400 rpm. The findings provide essential insights into the impact of fuel composition on engine power output:

- **Load-dependent torque behavior:** All types of fuels demonstrated a rise in BP as engine load increased, which aligns with the enhanced fuel delivery and combustion energy observed at elevated loads. Pure diesel (B0) reached its peak BP of 2.45 kW at 75% load, showcasing better performance in comparison to n-butanol blends.
- **Impact of n-butanol Blending:** Progressive BP reductions were observed with higher n-butanol content: B10: averagely 2.11% lower than B0, B20: averagely 5.76% lower than B0, B30: averagely 8.76% lower than B0 (showing the most significant decline).

Among these mixtures, B30 showed the lowest BP, which can be attributed to the reduced calorific value of n-butanol and its higher LHV. These factors may hinder peak combustion temperatures and reduce overall energy output. In contrast, B0 displayed better performance due to its lower viscosity and higher energy content, which promote more complete and efficient combustion.

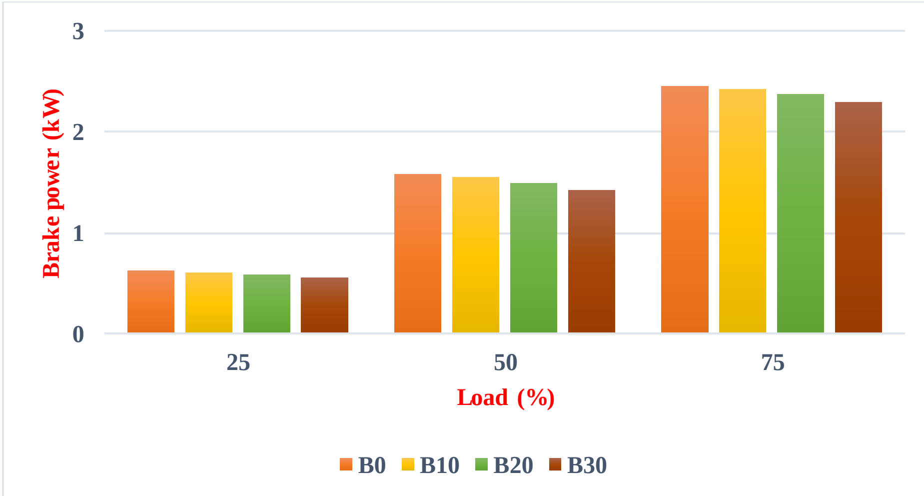


Figure 4.6 Effect of engine load on brake power

4.2.3. Brake specific fuel consumption (kg/kWh)

BSFC indicates fuel efficiency by quantifying the fuel required per unit of power produced, a key metric for assessing economic and environmental performance. Figure 4.7 illustrates the correlation between BSFC and engine load across various fuel blends, emphasizing significant efficiency trends:

- **Load-dependent efficiency trend:** BSFC initially decreases with rising load, reaching an optimal efficiency point at moderate loads (typically 50% load). This occurs because the engine achieves better thermal efficiency when operating closer to its design capacity, extracting more useful work per fuel unit. At high loads (around 75%), BSFC rises again due to: Increased fuel enrichment (more fuel injected than can be efficiently burned), potential oxygen limitations in the combustion chamber and higher heat losses from prolonged high-temperature operation
- **Fuel blend comparison:** B0 (pure diesel) demonstrated a 1.99% reduction in BSFC compared to B10, thereby affirming its marginal efficiency benefit under various conditions. Unexpectedly, the B20 and B30 blends displayed BSFC values that were 3.2% and 4.34% higher than B0, respectively—contradicting the anticipated performance of oxygenated fuels.

The reasons for the increased BSFC in n-butanol blends can be attributed to the fact that n-butanol possesses approximately 20% lower energy density compared to diesel. This characteristic necessitates a greater mass of fuel to generate an equivalent amount of power. Additionally, the high LHV results in a cooling effect on the air-fuel mixture, which in turn delays the vaporization process and hinders the propagation of the flame. Furthermore, the low cetane number associated with n-butanol leads to an extended ignition delay.

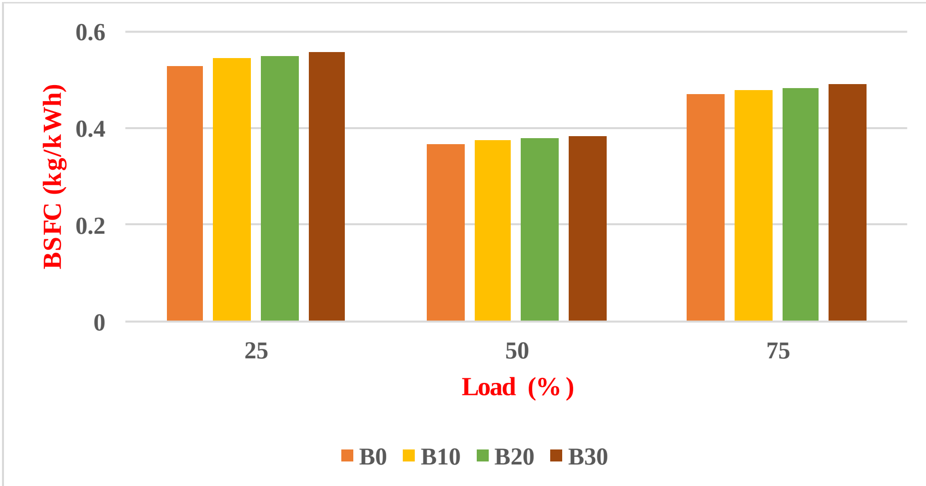


Figure 4.7 Effect of engine load on BSFC

4.3. Performance and emissions optimization through RSM techniques

The groundwork for a total of 13 experimental trials was laid out through a design matrix created using the central composite design (CCD) of RSM. This research concentrated on two key factors: engine load (X_1) and n-butanol ratio (X_2). The objective of the study was to examine both the individual and interactive effects of these factors on engine performance and emissions, utilizing RSM for this analysis. To assess the correlations and determine the influence of the input variables on the response variables, the statistical method of Analysis of Variance (ANOVA) was applied. The findings regarding engine performance, including BT, BP, and BSFC, as well as emissions such as NOx, CO_2, CO, and HC, were analyzed using ANOVA and are summarized in Table 4.1.

Table 4.1 Experimental matrix with the results of the engine performance and emission

Run	Variables		Results						
	load	n-butanol	BT (Nm)	BP (kW)	BSFC (kW/kgh)	CO_2 (vol.%)	NOx (ppm)	CO (vol.%)	HC (ppm)
1	25	10	2.43	0.60	0.546	2.73	43	0.044	47
2	75	30	6.41	2.29	0.491	3.84	201	0.040	46
3	15	20	3.03	0.49	0.586	2.29	31	0.051	53
4	25	20	2.37	0.58	0.551	2.65	40	0.046	50
5	50	20	4.20	1.49	0.379	3.36	145	0.033	27
6	50	20	4.21	1.50	0.380	3.37	147	0.034	28
7	80	20	6.55	2.37	0.488	4.05	219	0.042	44
8	50	0	4.29	1.58	0.368	3.50	162	0.030	24
9	50	20	4.19	1.48	0.378	3.35	144	0.033	27
10	25	30	2.34	0.55	0.556	2.57	38	0.048	52
11	50	10	4.25	1.55	0.375	3.42	151	0.031	25
12	50	30	4.12	1.42	0.384	3.25	141	0.036	29
13	75	10	6.64	2.42	0.478	4.01	211	0.037	41

4.3.1. Analysis of emissions using response surface methodology (RSM)

4.3.1.1. Nitrogen oxides and carbon dioxide emissions

The ANOVA for the quadratic model concerning NOx and CO_2 emissions is presented in Table 4.2. ANOVA significance is determined by the higher magnitude of the F-values, and the smaller value of P-value, typically less than 0.05. The results of the ANOVA analysis revealed that the X1 and X2 variables are significant factors in affecting the emissions of both NOx and CO_2. Specifically, X_1 term exerts the most substantial effect on NOx with a highly significant F-value of 330.53 and P-value of 0.0001. The X_2 term also substantial affects NOx emissions, due to an F-value of 19.73 and a P-value of 0.001. Additionally, the quadratic terms X_1^2 are significant, due to an F-value of 4.83 and P-value of 0.024. In terms of CO_2 emission, both the X_1 term (P-value = 0.0001, F-value = 10587.30) and the X_2 term (P-value = 0.0001 and F-value = 150.53) are once more discovered to exert significant effects. The interaction term X_1X_2 shows a small significant influence on both CO_2 and NOx emissions. The numerical relationship between the responses (NOx and CO_2) and the process factors was formulated and provided in Equation 4.1 and 4.2. It provides a second-order polynomial model demonstrating the relationship between the investigated factors (such as engine load and n-butanol) and the process responses (NOx and CO_2).

$$\text{NOx (ppm)} = -53.6 + 5.157X_1 - 0.49X_2 - 0.01928X_1^2 + 0.0031X_2^2 - 0.005X_1{*}X_2 \quad (4.1)$$

$$CO_2\,(\%\text{vol.}) = 1.9189 + 0.03703X_1 - 0.0052X_2 - 0.000109X_1^2 - 0.00068X_2^2 - 0.00001X_1{*}X_2 \quad (4.2)$$

Table 4.2 ANOVA for engine emissions

Source	CO_2		NOx		CO		HC	
	P-value	F-value	P-value	F-value	P-value	F-value	P-value	F-value
Model	0.0001	2337.07	0.0001	73.97	0.0001	58.59	0.001	15.18
X_1	0.0001	10587.30	0.0001	330.53	0.0001	40.08	0.156	2.53
X_2	0.0001	150.53	0.001	19.73	0.005	16.08	0.115	3.24
X_1^2	0.0001	72.00	0.024	4.83	0.0001	161.92	0.0001	56.51
X_2^2	0.280	1.37	0.939	0.01	0.609	0.29	0.498	0.51
$X_1 \times X_2$	0.787	0.08	0.843	0.04	0.726	0.13	1.00	0.00

The mixed effects of engine load and n-butanol content on NOx emissions are shown in Figure 4.8. It was discovered that while NOx levels increase as engine speed increases, NOx emissions are reduced at lower loads due to a drop-in combustion temperature. In particular, Figure 4.8 shows that NOx decreases as n-butanol content increases (for example, at 50% load, the NOx level decreased from 162 ppm at 0% n-butanol to 141 ppm at 30% n-butanol). At a 15% load with B20, the lowest NOx emissions were 31 ppm.

The significant latent vaporization linked to the low reactivity of n-butanol fuel is responsible for the decrease in NOx emissions. This characteristic lowers the cylinder temperature, which reduces the amount of NOx emissions produced (Ganesan et al., 2020). Furthermore, Figure 4.9 shows how engine load and n-butanol content interact with regard to CO_2 emissions. It was shown that CO_2 emissions increase as load increases, but emissions decrease when n-butanol content is high. This decrease is probably due to the increased combustion efficiency that n-butanol's oxygen content providers. With a B20 blend, the lowest CO2 emission level (2.29% vol.) was attained at 15% engine load.

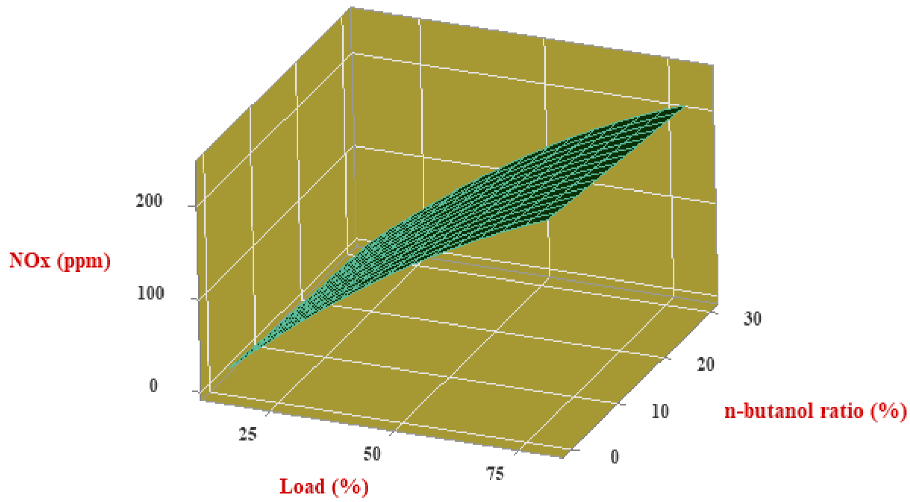


Figure 4.8 NOx vs engine load and n-butanol ratio

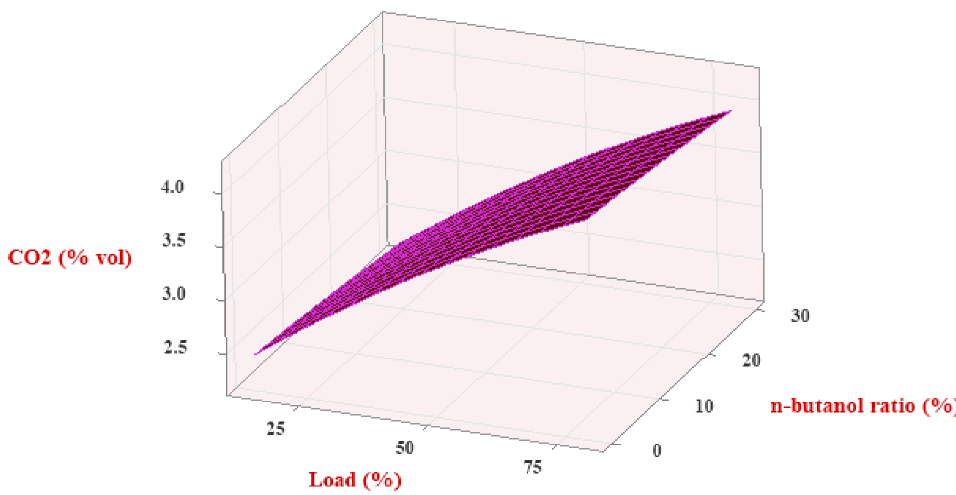


Figure 4.9 CO_2 vs engine load and n-butanol ratio

4.3.1.2. Carbon monoxide and hydrocarbons emissions

The ANOVA for the quadratic model concerning CO and HC emissions is presented in Table 4.2. The ANOVA analysis indicates that X_1 term has the most substantial impact on both CO and HC emissions, with P-values of 0.0001 and an F-value of 15.18 for HC and 58.59 for CO, indicating strong linear effects. In contrast, the X_2 term shows an insignificant impact on HC emissions, with an F-value (2.33) and a P-value (0.156), while its impact on CO emission is has significant, reflected in a P-value of 0.0001 and an F-value of 40.08. Notably, the quadratic term X_1^2 is more significant for HC, as shown by a P-value of 0.0001 and an F-value of 56.51, compared to CO, which has a P-value of 0.0001 and an F-value of 161.92. The numerical relationship between the responses (HC and CO) and the process factors was formulated and provided in Equation 4.3 and 4.4. It provides a second-order polynomial model demonstrating the relationship between the investigated factors (such as engine load and n-butanol) and the process responses (HC and CO).

$$HC\ (ppm) = 89.3 - 2.436X_1 - 0.102X_2 + 0.02341X_1^2 + 0.01X_2^2 - 0.00000001X_1*X_2 \qquad (4.3)$$

$$CO\ (\%vol.) = 0.06696 - 0.001362X_1 + 0.000166X_2 + 0.000013X_1^2 + 0.000002X_2^2 - 0.0000001X_1*X_2 \quad (4.4)$$

The impact of input parameters, especially engine load and n-butanol concentration, on CO and HC emissions is shown in Figures 4.10 and 4.11. The combined impacts of engine load and n-butanol content on HC emissions are shown in Figure 4.10. It was found that while the level of HC increases as engine speed increases, emissions of HC are reduced at lower loads due to a decrease in combustion temperature. In particular, Figure 4.10 shows that HC rises with n-butanol content (for example, at 50% load, the HC level increased from 24 ppm at 0% of n-butanol to 29 ppm at 30% of n-butanol).

At 50% load with B0, the lowest HC emissions were 24 ppm. Additionally, Figure 4.11 indicates how engine load and n-butanol content interact with regard to CO emissions. A high percentage of n-butanol causes an enhance in emissions, but it was found that CO emissions decreased with increasing load. This increase is probably caused by incomplete combustion, which is made possible by the oxygen in n-butanol. With a B0 blend, the lowest CO emission level (0.030% vol.) was achieved at 50% engine load.

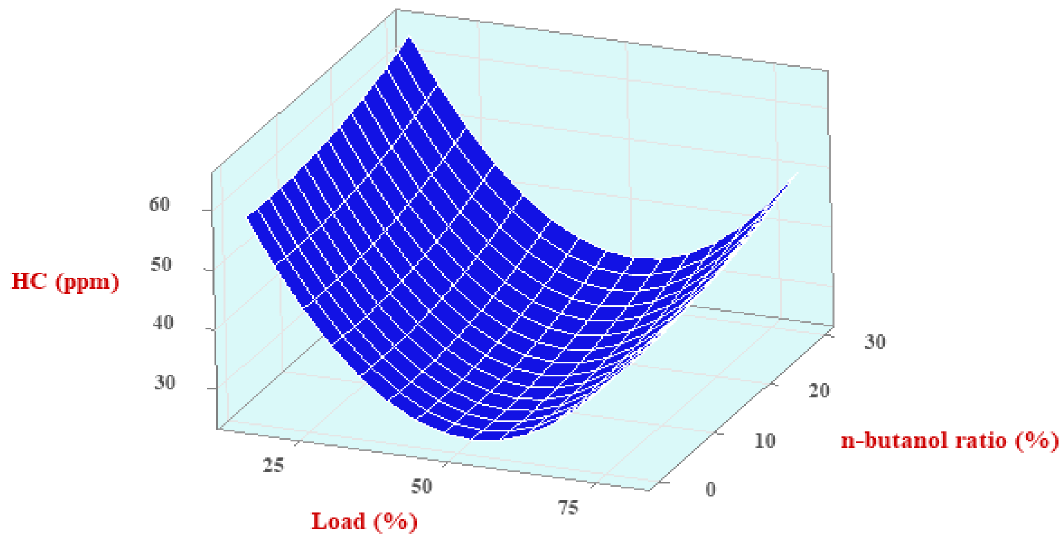


Figure 4.10 HC vs engine load and n-butanol ratio

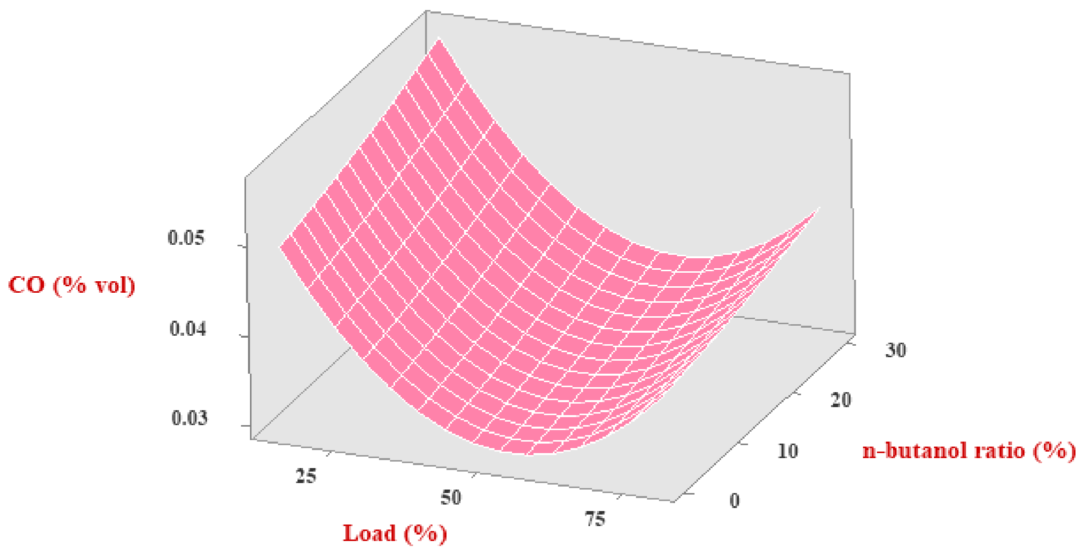


Figure 4.11 CO vs engine load and n-butanol ratio

4.3.2. Analysis of performance using response surface methodology (RSM)

4.3.2.1. Brake Torque

Brake torque (BT) is the engine's torque measured at the crankshaft or input shaft while taking internal resistive forces like friction into account. The ANOVA analysis shown in Table 4.3 indicates that X_1 has a substantial effect on the BT, evidenced by a P-value of 0.0001 and significant F-values (194.39) that imply a meaningful impact. Additionally, the term related to X_1^2 shows a strong level of significance, with an F-value of 6.59 and a P-value of 0.037. Conversely, the terms X_2, X_2^2, and X_1X_2 seem to exert a minimal influence on the overall response. The numerical relationship between the responses (BT) and the process factors was formulated and provided in equation 4.5. It provides a second-order polynomial model demonstrating the relationship between the investigated factors (such as engine load and n-butanol) and the process response (BT).

$$BT\ (Nm) = 2.17 + 0.0073X_1 + 0.0033X_2 + 0.000686X_1^2 - 0.00013X_2^2 - 0.00014X_1{*}X_2 \quad (4.5)$$

Table 4.3 ANOVA for engine performance

Source	BT		BP		BSFC	
	P-value	F-value	P-value	F-value	P-value	F-value
Model	0.0001	39.00	0.0001	130.17	0.001	17.76
Load (X_1)	0.0001	194.39	0.0001	625.17	0.028	7.59
n-butanol X_2)	0.55	0.39	0.174	2.29	0.377	0.89
X_1^2	0.037	6.59	0.002	11.28	14.92	0.04
X_2^2	0.916	0.01	0.955	0.00	0.597	0.31
$X_1 \times X_2$	0.855	0.04	0.681	0.18	0.961	0.00

Moreover, the relationship between engine load and the concentration of n-butanol on BT is shown in Figure 4.12, explaining that BT is relatively increasing from 2.34 Nm to 6.64 Nm. BT gives its highest torque value of 6.64 Nm when it is subjected to a 75% engine load with a concentration of B10. Nevertheless, as the concentration factor of n-butanol is increased to its highest point of 30% for the same load condition, BT lowers to its minimum torque value of 6.41 Nm due to the minimum calorific value of n-butanol.

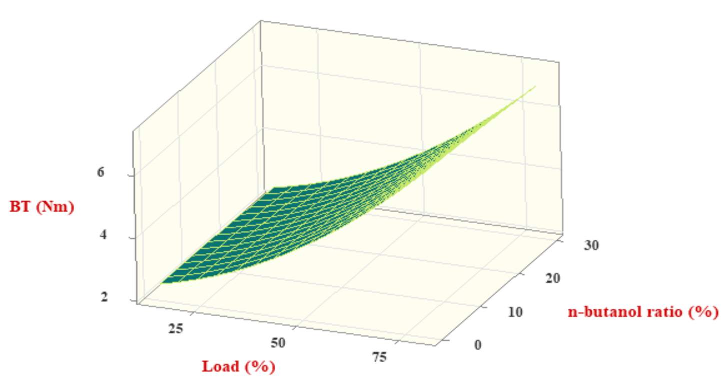


Figure 4.12 BT vs engine load and n-butanol ratio

4.3.2.2 Brake Power

The effective power output of an engine, measured at the output shaft, is known as brake power (BP). This measurement takes into consideration the losses brought on by friction and other internal engine BP components. Table 4.3 clearly demonstrates that the X_1 term has a significant impact on BP, with highly significant P-values (0.0001) and F-values of 625.17. In addition, with an F-value of 11.28 and a P-value of 0.002, the term tied to X_1^2 shows a high degree of significance. The X_2, X_2^2, and X_1X_2 terms, on the other hand, seem to have little effect on the response as a whole. The engine load has significant impact on blood pressure because higher loads typically increase blood pressure by allowing more fuel combustion per unit of time. However, excessively high speeds may decrease efficiency because of increased friction and incomplete combustion. Equation 4.6 presents the numerical relationship that was developed between the responses (BP) and the process factors. It offers a second-order polynomial model that illustrates the connection between the process response (BP) and the factors under investigation (such as engine load and n-butanol).

$$BP\ (kW) = -0.11 + 0.0327X_1 - 0.0007X_2 + 0.000019X_1^2 - 0.000018X_2^2 - 0.00008X_1{*}X_2 \quad (4.6)$$

Figure 4.13 shows the relationship between engine load and the n-butanol ratio on BP. According to the results, BP typically increases as engine load increases, specifically between 25% (0.55 kW) and 75% (2.42 kW). Furthermore, because butanol has a lower energy density, BP decreases as the n-butanol ratio increases; for example, at 50% load, BT decreases from 1.58 kW at 0% of n-butanol to 1.42 kW at 30% n-butanol. At 75% load and 10% n-butanol content, the peak BP of 2.42 kW was achieved.

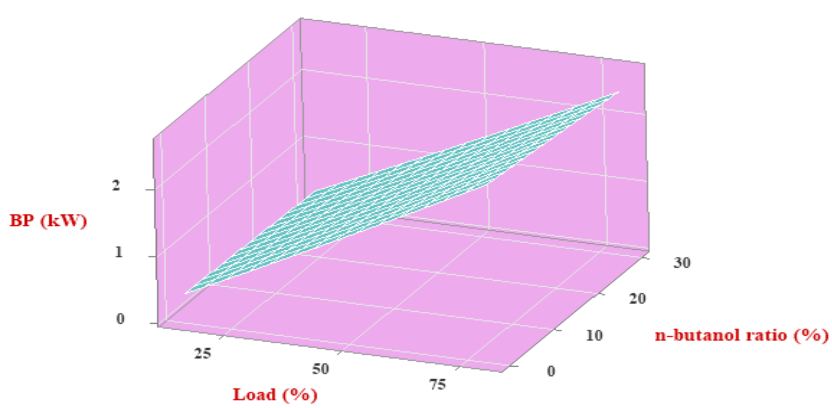


Figure 4.13 BP vs engine load and n-butanol ratio

4.3.2.3. Brake specific energy consumption

A key engine metric is BSFC, which is the quantity of fuel used per unit of power produced over a given time period. Both the heating value of the fuel and its particular fuel consumption have an effect on this parameter. The importance of this analysis is especially clear when comparing different fuels with different cetane numbers and heating values. BSFC is significantly impacted by the X_1 term, according to the ANOVA results shown in Table 4.3, highlighting their crucial contributions to engine performance. A highly significant F-value of 7.59 shows that X_1 has a significant impact on BSFC. Additionally, with an F-value of 14.92 and a P-value of 0.04, the term assigned to X12 shows a high degree of significance. The X_2, X_2^2, and X_1X_2 terms, on the other hand, seem to have less effect on the response as a whole. Equation 4.7 presents the numerical relationship that was developed between the responses (BSFC) and the process factors. It provides a second-order polynomial model that illustrates the connection between the process response (BSFC) and the factors under investigation, such as engine load and n-butanol.

$$\text{BSFC (kg/kWh)} = 0.8718 - 0.01829X_1 - 0.0012X_2 + 0.000171X_1^2 + 0.000053X_2^2 + 0.000003X_1{*}X_2 \quad (4.7)$$

Figure 4.14 shows how engine load and n-butanol ratio interact with regard to BSFC. These plots show that BSFC rises as n-butanol content rises because of a lower energy density, which requires a larger fuel volume to produce the same power output. Higher engine loads, on the other hand, require less fuel to maintain the required power levels. At 50% load, a B10 blend produced the lowest BSFC of 0.375 kg/kWh.

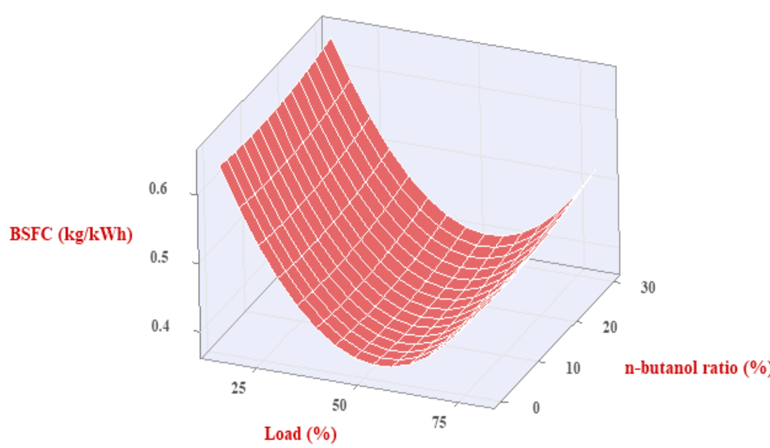


Figure 4.14 BSFC vs engine load and n-butanol ratio

4.3.3. RSM based optimization

The principal aim of optimization in engineering systems is to locate the most favorable set of variables that gives the optimal outcome either by maximizing desired outcomes or minimizing undesirable ones within a given range of input conditions. There are numerous distinct methods to employ for that purpose, particularly with multiple inputs and responses. RSM, a statistical and mathematical modeling approach, is very suitable for such complex systems. It allows the concurrent investigation of a group of input and output variables and determines the best conditions by creating empirical relations. In this study, RSM was selected due to the presence of greater than one factor with effect and multiple dependent responses. Regarding the actual key design variables, engine load (X_1) and n-butanol blending ratio (X_2) were utilized. The optimization procedure was focused on maximizing the performance of the engine: via optimization of BT and BP and simultaneously reducing BSFC and exhaust emissions such as NOx, CO, HC, and CO_2.

Figure 4.15 illustrates the optimization setup applied in the RSM environment with the input parameters limited within experimental practical upper and lower bounds. The optimizer was programmed to optimize or maximize the target responses based on defined objectives. Figure 4.16 illustrates the results of the optimization process with the best engine operating conditions ascertained. Optimal performance-emission trade-off was achieved by 49.79% engine load and 10% blend ratio of n-butanol at RSM optimization output. Under these conditions, the engine delivered a brake torque of 4.18 Nm and brake power of 1.52 kW. BSFC was reduced to 0.379 kg/kWh based on efficiency. The quality of emissions also significantly improved, with carbon dioxide emissions at 3.427 %vol, carbon monoxide at 0.0318 %vol, nitrogen oxides at 148 ppm, and hydrocarbons at 26 ppm. These results underscore the critical roles of engine load and fuel composition in an engine's behavior. Optimized, it guarantees that a moderate engine load with an appropriately tuned n-butanol blend can significantly enhance overall engine performance while reducing environmental contaminants. Moreover, RSM's ability to identify such harmonious operating conditions renders it an effective predictive and decision-support tool in multi-objective optimization problems involving ICEs.

Response	Goal	Lower	Target	Upper	Weight	Importance
HC	Minimize	24	24	53	1	1
CO	Minimize	0.03	0.03	0.051	1	1
NOx	Minimize	31	31	219	1	1
CO2	Minimize	2.29	2.29	4.05	1	1
BSFC	Minimize	0.368	0.368	0.586	1	1

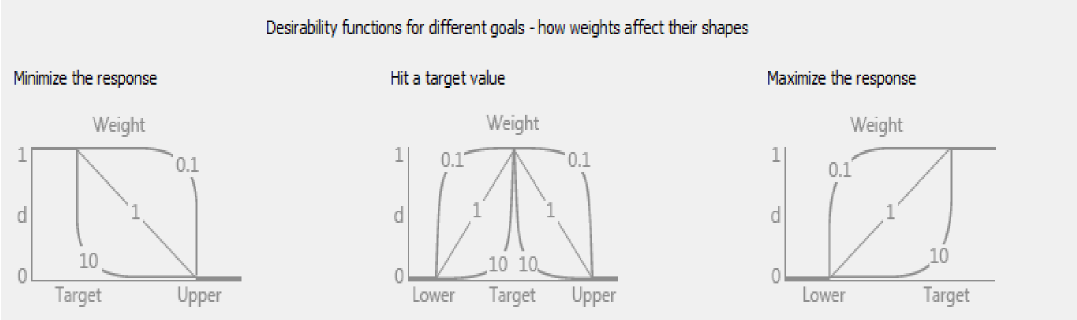


Figure 4.15 Optimization setup

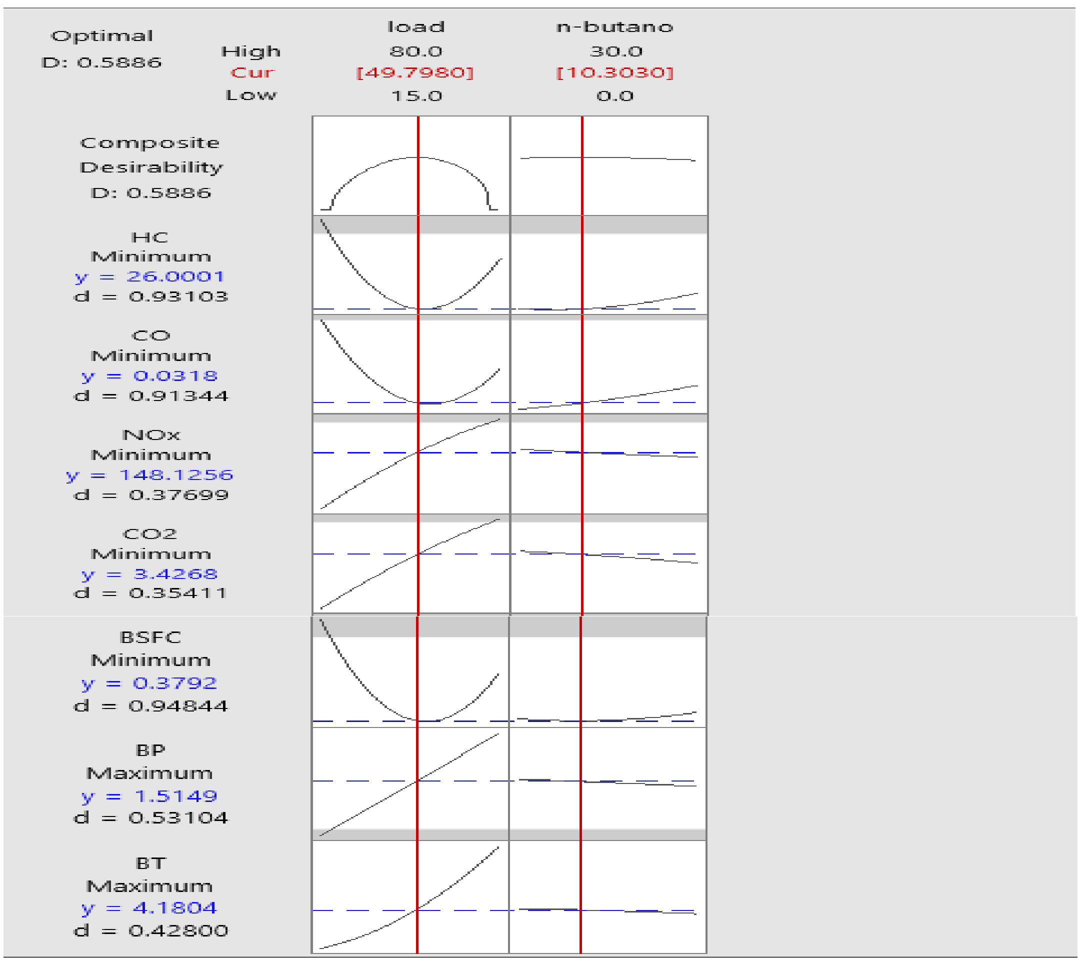


Figure 4.16 Optimization results

4.4. Statistical analysis using artificial neural networks techniques

In this study, an ANN model was developed to predict the performance and emission characteristics of CI engine under various operating conditions. The architecture of ANN comprised two input neurons, ten neurons in a hidden layer, and seven output neurons (2-10-7). The input layer consisted of engine load and the percentage of n-butanol blended with the base fuel, while the output layer included key engine performance and emissions: BP, BT, BSFC, NOx, CO_2, and CO, as depicted in Figure 4.17. The ANN was trained using experimental data gathered during the engine trials. During the training phase, the model exhibited high predictive performance with correlation coefficients (R-values) of 0.99829 for training, 0.0981 for validation, and 0.99576 for testing. When all data sets were combined, the overall R-value was 0.99621, indicating a very strong linear relationship between the experimental and predicted outputs. These high R-values signify that the ANN accurately captured the complex nonlinear relationships among the input and output variables. Furthermore, the mean squared error was minimized to 15.6733 at the sixth epoch during validation, signify a rapid convergence and effective learning during training, further confirming the ANN model's robustness in reproducing experimental trends with remarkable precision.

Importantly, the uniformity of R-values and low MSE across training, validation, and testing datasets indicates that the model neither suffers from underfitting nor overfitting. This balance highlights the ANN's ability to generalize well across unseen data, making it a reliable predictive tool for estimating engine performance and emissions under varied conditions. Figures 4.18 and 4.19 illustrate the ANN's predictive accuracy and regression performance, further confirming the model's strong agreement with experimental results. Overall, the results validate the effectiveness of ANN as a powerful and accurate modeling tool for complex engine systems, especially when dealing with multiple interacting variables such as fuel composition and load variation.

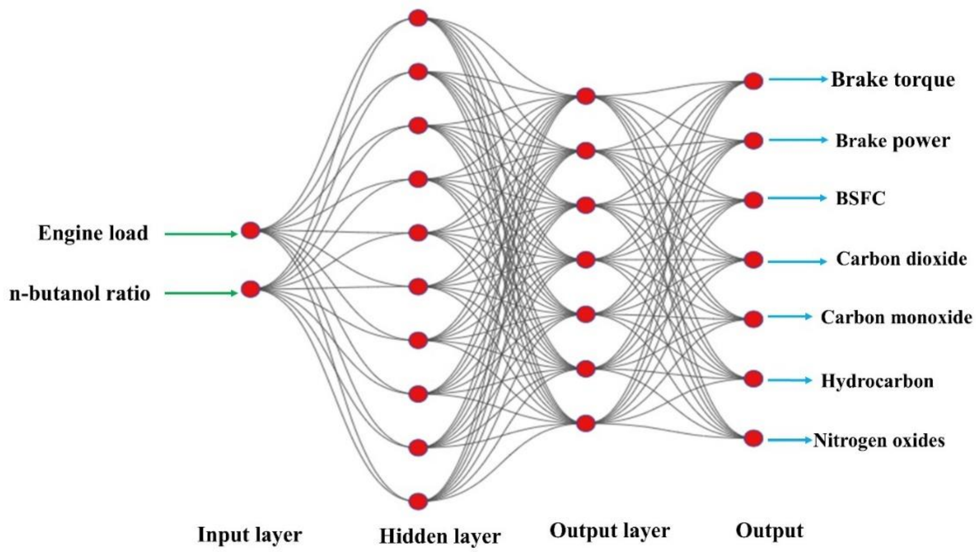


Figure 4.17 Input, hidden, and output layers of the ANN model

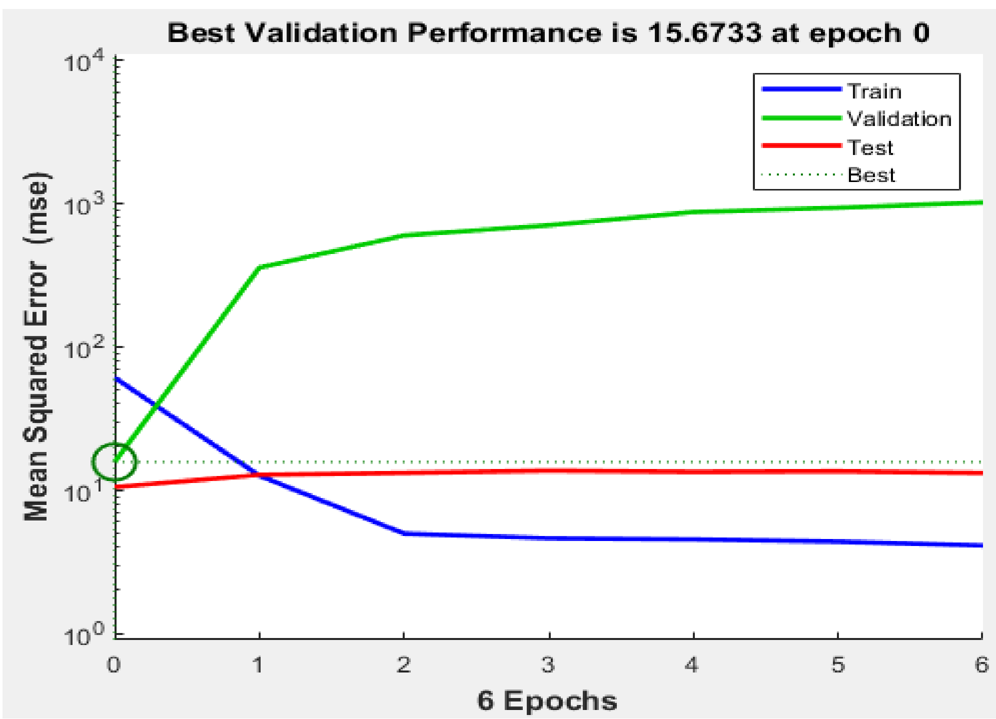


Figure 4.18 Performance of ANN model

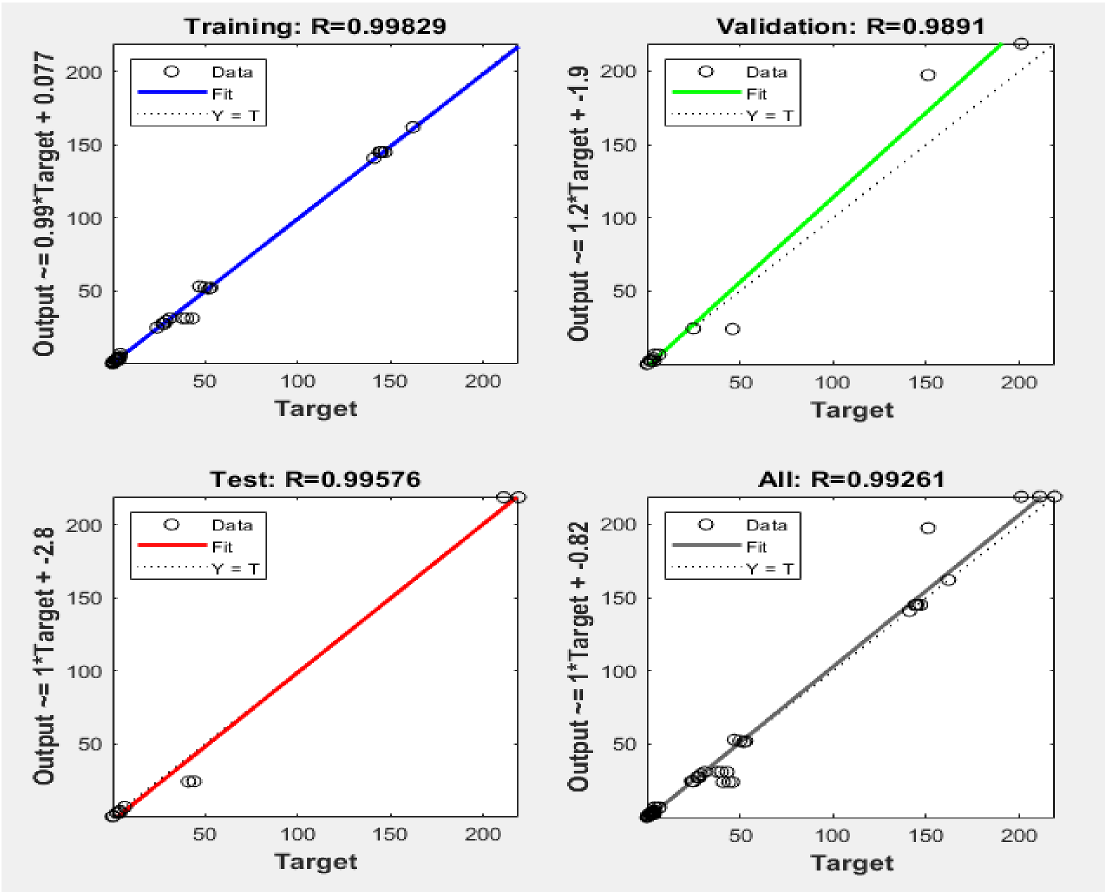


Figure 4.19 Regression analysis of ANN model

4.5. Comparison analysis of RSM and ANN

To evaluate and compare the predictive performance of the RSM and ANN models, key statistical indicators: R^2, MSE, and RMSE were employed. These metrics, defined by Equations (3.2), (3.3), and (3.4), provide a comprehensive assessment of how well each model replicates the experimental data. The R^2 value quantifies the proportion of variance in the observed data that is explained by the model. A value close to 1 implies an excellent fit and strong predictive accuracy. MSE measures the average of the squared differences between predicted and actual values; thus, a lower MSE indicates higher prediction precision. RMSE, expressed in the same units as the target output, offers an intuitive measure of prediction error magnitude and is especially useful for comparing model accuracy across different parameters.

As detailed in Table 4.4, the predictive performance of both ANN and RSM was evaluated for key engine performance indicators: BT, BP, and BSFC. Both models demonstrated high R^2 values, reflecting their reliability; however, ANN consistently achieved marginally higher accuracy. For instance, ANN recorded R^2 values of 0.9936 and 0.9997 for BT and BP, respectively, while RSM achieved 0.983 and 0.995. When predicting BSFC, which generally more sensitive to fuel blend and load conditions, both models yielded good R^2 values 0.9766 for ANN and 0.963 for RSM, yet ANN again offered better fit to the observed data. The error-based metrics also reinforce the conclusion that ANN marginally outperforms RSM. In predicting BP, ANN achieved lowest MSE and RMSE values (0.0004 and 0.0202, respectively), significantly better than RSM's 0.0047 MSE and 0.0684 RMSE. A similar trend was observed in BT prediction. Where ANN showed reduced error levels (MSE: 0.0301, RMSE: 0.1736) compared to RSM (MSE: 0.0738, RSME: 0.2716). Interestingly, ANN demonstrated slightly better performance in BSFC prediction based on MSE (0.0005 vs 0.00039), although RMSE values remained comparable between both models (ANN: 0.0196, RSM: 0.0217). This indicates that ANN can effectively handle certain nonlinearities in fuel consumption trends.

Figures 4.20, 4.21, and 4.22 illustrate the comparative performance of the models by plotting the experimentally measured values of BT, BP, and BSFC against those predicted by ANN and RSM. The visual representation further confirms that both models closely follow the experimental data, with ANN slightly outperforming RSM in terms of fitting accuracy and trend replication. These findings underscore the reliability of both methods for predictive modeling; however, ANN may offer a slight advantage when modeling engine performance characteristics.

Table 4.4 RSM and ANN model comparison for engine performance

Function	Parameter	RSM	ANN
R^2	Brake torque	0.983	0.9936
	Brake power	0.995	0.9997
	BSFC	0.963	0.9766
MSE	Brake torque	0.0738	0.0301
	Brake power	0.0047	0.0004
	BSFC	0.0005	0.00039
RMSE	Brake torque	0.2716	0.1736
	Brake power	0.0684	0.0202
	BSFC	0.0217	0.0196

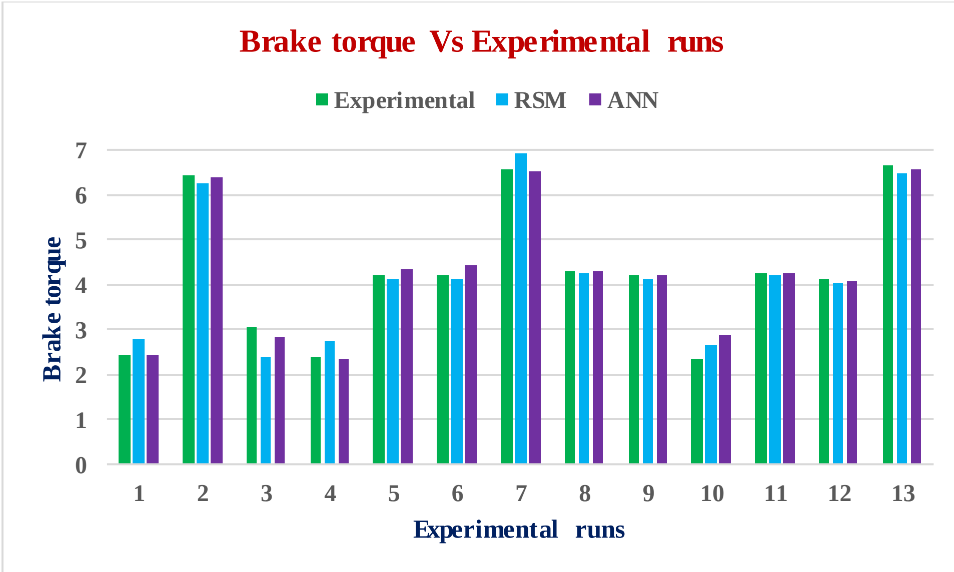


Figure 4.20 Comparison of BT result with RSM and ANN model

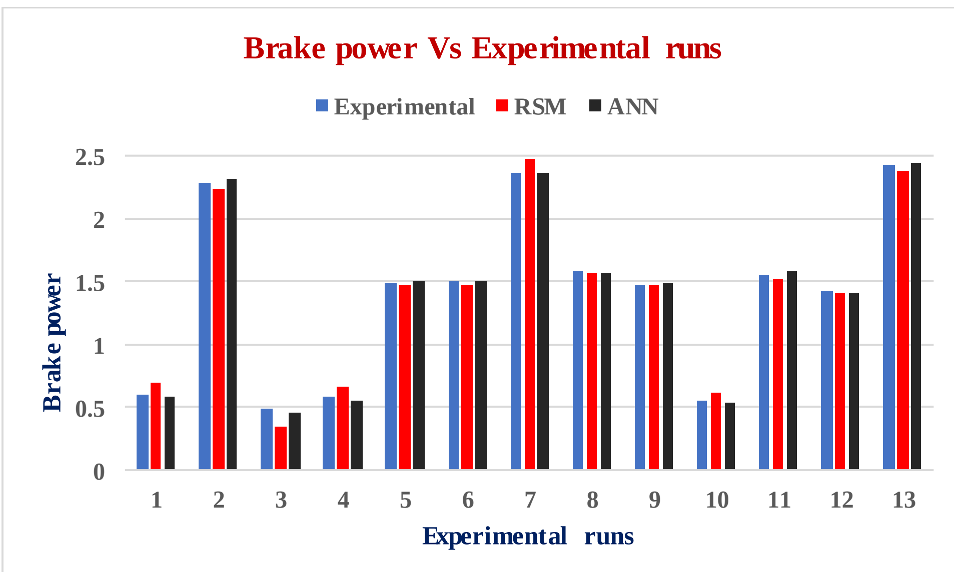


Figure 4.21 Comparison of BP result with RSM and ANN model

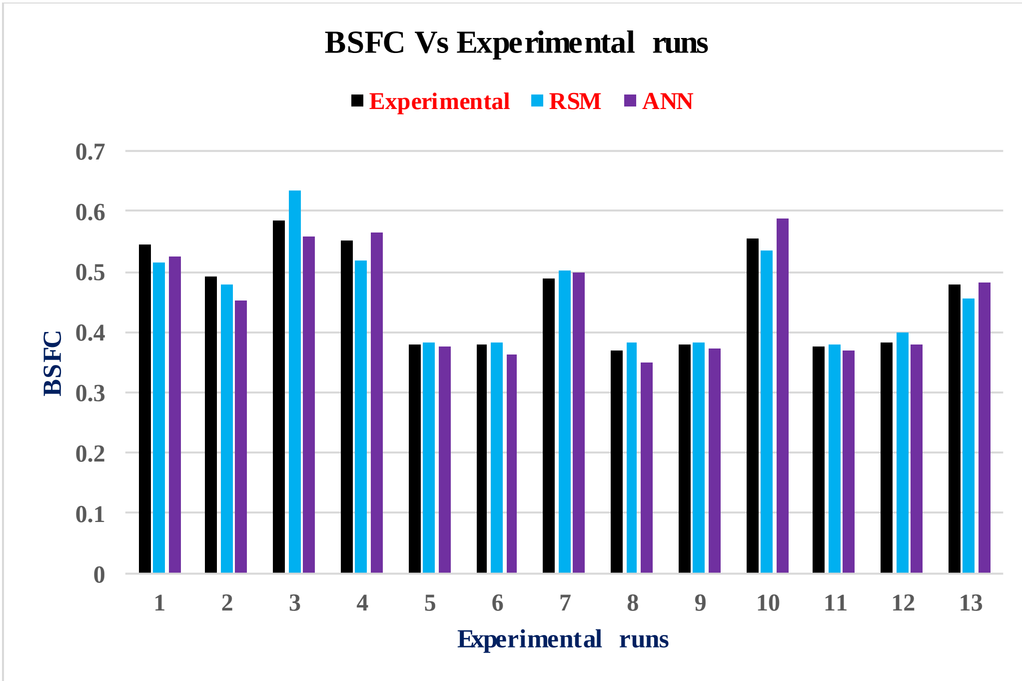


Figure 4.22 Comparison of BP result with RSM and ANN model

Table 4.5 presents a comparative analysis between the ANN and RSM models for predicting engine emission characteristics, specifically CO_2, NOx, CO and HC. Both models demonstrated outstanding performance in predicting CO_2 and NOx, with R^2 value of 0.999 for both parameters, indicating an almost perfect correlation between predicted and actual values. For CO, RSM significantly outperformed RSM with an R^2 of 0.988 compared to ANN's 0.975, showing that RSM is more effective in capturing the nonlinear behavior of CO emissions. Furthermore, in the case of HC emissions, ANN slightly edged out RSM with an R^2 of 0.9934 versus 0.987, suggesting that ANN provided a marginally better fit for HC prediction. The error metrics MSE and RMSE, further clarify the strengths and weakness of each model. For CO^2 emissions, both models showed minimal error, with ANN achieving slightly better performance (MSE: 0.0001, RSME: 0.0119) than RSM (MSE: 0.0002, RMSE: 0.0131). a notable difference appears in the prediction of NOx emissions, where ANN performed far better, with a significantly lower MSE of 3.0911 compared to RSM's high MSE of 4.939, indicating that ANN provided a marginally better fit for NOx prediction. For CO prediction, RSM outshined ANN with a lower MSE (1.01E-06 vs 2.53E-0.6) and RMSE (0.001 vs 0.0016). lastly in the case of HC emissions, ANN showed better predictive accuracy with lower MSE and RMSE values (2.422 and 1.56, respectively) compared to RSM (3.648 and 1.91). overall, the results suggest that while both models are highly effective for emission prediction, ANN exhibits superior performance in capturing highly nonlinear emission trends like CO_2, HC, and NOx, whereas RSM shows better consistency in modeling CO emission.

Figures 4.23, 4.24, 4.25, and 4.26 depict the comparative emissions of the models by graphing the experimentally obtained values of CO_2, NOx, CO, and HC against the predictions made by ANN and RSM. This visual representation further validates that both models closely align with the experimental data, with ANN demonstrating a marginally superior performance compared to RSM regarding fitting accuracy and trend replication. These results highlight the dependability of both approaches for predictive modeling; nonetheless, ANN may provide a slight edge in modeling engine emission characteristics.

Table 4.5 RSM and ANN model comparison for engine emission

Function	Parameter	RSM	ANN
R^2	Carbon dioxide	0.999	0.999
	Nitrogen oxides	0.999	0.999
	Carbon monoxide	0.988	0.975
	Hydrocarbons	0.987	0.9934
MSE	Carbon dioxide	0.0002	0.0001
	Nitrogen oxides	4.939	3.0911
	Carbon monoxide	1.01E-06	2.53E-06
	Hydrocarbons	3.648	2.422
RMSE	Carbon dioxide	0.0131	0.0119
	Nitrogen oxides	2.292	1.758
	Carbon monoxide	0.001	0.0016
	Hydrocarbons	1.91	1.56

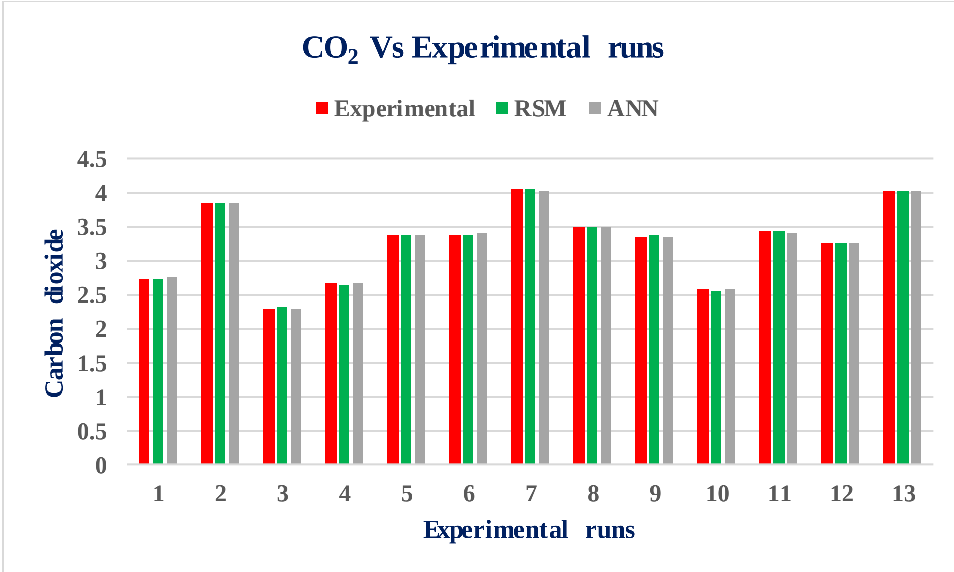


Figure 4.23 Comparison of CO_2 result with RSM and ANN model

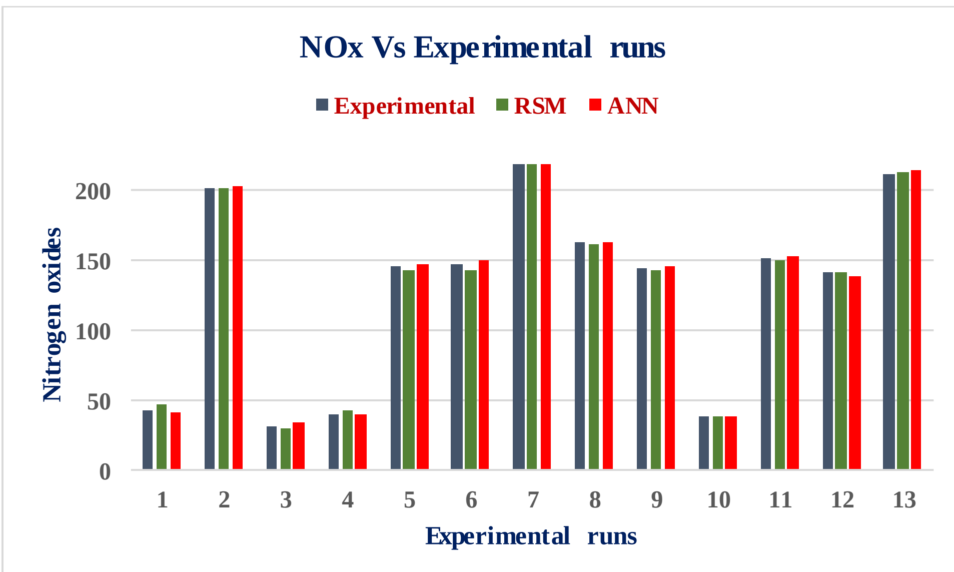


Figure 4.24 Comparison of NOx result with RSM and ANN model

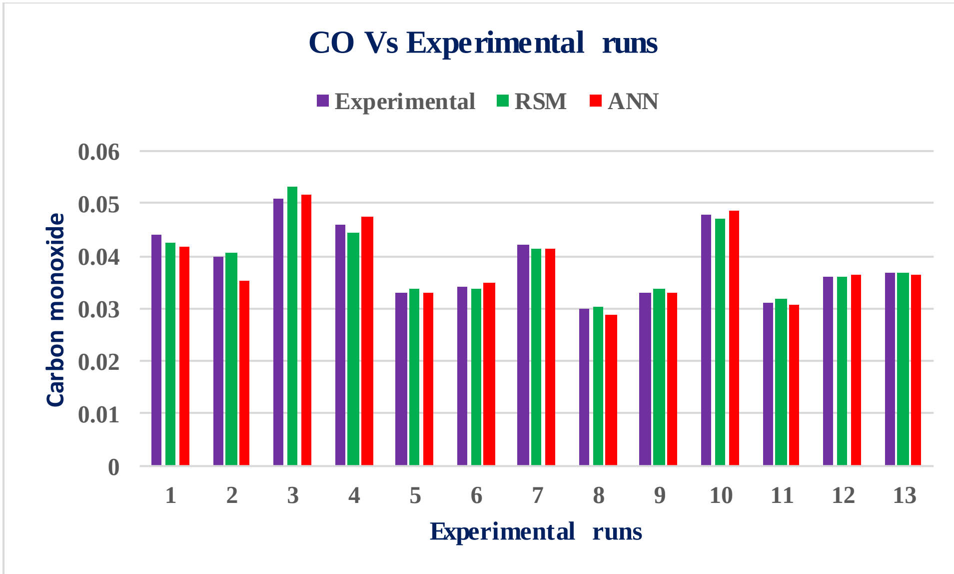


Figure 4.25 Comparison of NOx result with RSM and ANN model

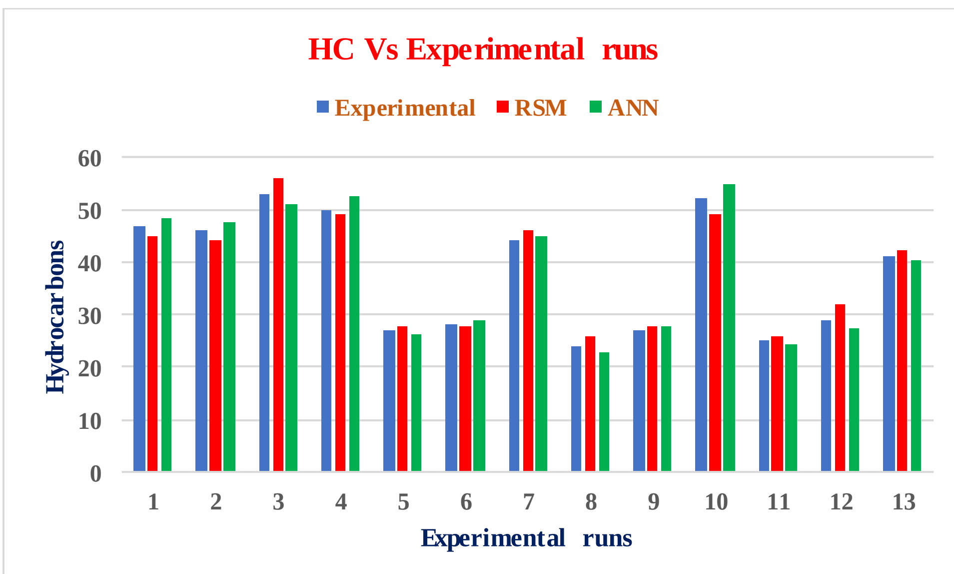


Figure 4.26 Comparison of HC result with RSM and ANN model

CHAPTER FIVE

CONCLUSIONS AND RECOMMEDATION

5.1. Conclusions

In this study, diesel-n-butanol blends were used to optimize a CI engine's performance and emission characteristics using RSM and ANN techniques. The following summarizes the main findings:

- All experimental work was conducted at Addis Ababa Science and Technology University (AASTU).
- Test fuels included pure diesel (B0) and blends with 10%, 20%, and 30% (B10, B20, and B30).
- Among all tested blends, B10 showed the most balanced performance, with substantial emission reductions and minimal loss in engine power. It significantly reduces CO_2 and NOx while maintaining BT and BP to standard diesel.
- A numerical optimization process using CCD was employed in RSM to identify ideal operating parameters. The optimization targeted maximizing BT and BP, while minimizing BSFC, CO, CO_2, NOx, and HC.
- The optimal condition was identified at engine load of 49.79% and n-butanol ratio of 10.30%. Under these setting, the engine delivered: BT (4.18 Nm), BP (1.52 kW), BSFC (0.379 kg/kWh), CO_2 (3.4277 %vol.), CO (0.0318 %vol.), NOx (148 ppm) and HC (26 ppm).
- Both RSM and ANN models successfully predicted engine performances and emissions under varying input conditions. ANN outperformed RSM, with higher R2 values and lower MSE and RMSE, indicating better predictive reliability. The combination of statistical and machine learning based models offers a powerful hybrid approach to optimization.
- Optimized use of n-butanol as oxygenated fuel additive can significantly reduce harmful emissions without compromising engine power. The findings contribute to the ongoing global efforts to develop sustainable fuel alternatives and meet environmental regulations.

5.2. Recommendations and Future Directions

Several suggestions and directions for further research are made in light of the study's findings in order to improve the understanding and optimization of diesel engine performance through the use of alternative fuel blends:

A crucial recommendation involves the incorporation of in-cylinder pressure measurement alongside HRR analysis to create a more robust link between combustion events and engine performance. Such understanding can enhance the precision of models and aid in identifying combustion inefficiencies. Furthermore, although RSM and ANN have proven successful in refining engine parameters, the addition of other sophisticated optimization methods like Genetic Algorithms, Particle Swarm Optimization, or Adaptive Neuro-Fuzzy Inference System (ANFIS) could lead to better predictive performance and optimization results.

Future studies ought to investigate the improvement of diesel–n-butanol fuel mixtures by incorporating metal oxide nanoparticles like CuO, Al_2O_3, TiO_2, CeO_2 etc. The inclusion of these additives has the potential to enhance combustion properties by facilitating superior fuel atomization and catalytic performance, which may result in heightened thermal efficiency and diminished emissions. It is advisable to conduct additional research into the combustion dynamics of these sophisticated blends; encompassing ignition delay, combustion duration, and flame propagation, to comprehensively grasp their effects on engine performance.

Future research should also focus on the practical considerations of fuel blend utilization, such as the long-term wear on engines, the stability of blends during storage, and their performance across different load and speed scenarios. It is also advisable to broaden emission characterization to include pollutants beyond the standard ones and to create hybrid modeling techniques that integrate both physical and AI-driven models. These strategies will enhance prediction accuracy and foster a more comprehensive understanding of combustion processes and the environmental effects of alternative fuels.

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APPENDICES

Appendix A: Engine performance and emissions data

(reference or baseline fuel)

Engine load	BT (Nm)	BP (kW)	BSFC (kg/kWh)	CO_2 (% vol)	NOx (ppm)	CO (% vol)	HC (ppm)
25	2.46	0.62	0.531	2.81	48	0.042	45
50	4.29	1.58	0.368	3.50	162	0.030	24
75	6.75	2.45	0.472	4.12	227	0.035	38

Sample 1 (B10 (90% diesel and 10% n-butanol)

Engine load	BT (Nm)	BP (kW)	BSFC (kg/kWh)	CO_2 (% vol)	NOx (ppm)	CO (% vol)	HC (ppm)
5	2.35	0.41	0.762	2.02	22	0.059	55
25	2.43	0.60	0.546	2.73	43	0.044	47
50	4.25	1.55	0.375	3.42	151	0.031	25
75	6.64	2.42	0.478	4.01	211	0.037	41

Sample 2 (B20 (80% diesel and 20% n-butanol)

Engine load	BT (Nm)	BP (kW)	BSFC (kg/kWh)	CO_2 (% vol)	NOx (ppm)	CO (% vol)	HC (ppm)
15	3.03	0.49	0.586	2.29	31	0.051	53
25	2.37	0.58	0.551	2.65	40	0.046	50
50	4.20	1.49	0.379	3.36	145	0.033	27
75	6.50	2.34	0.485	3.95	205	0.038	43
80	6.55	2.37	0.488	4.05	219	0.042	44

Sample 3 (B30 (70% diesel and 30% n-butanol)

Engine load	BT (Nm)	BP (kW)	BSFC (kg/kWh)	CO_2 (% vol)	NOx (ppm)	CO (% vol)	HC (ppm)
25	2.34	0.55	0.556	2.57	38	0.048	52
50	4.12	1.42	0.384	3.25	141	0.036	29
75	6.41	2.29	0.491	3.84	201	0.040	46

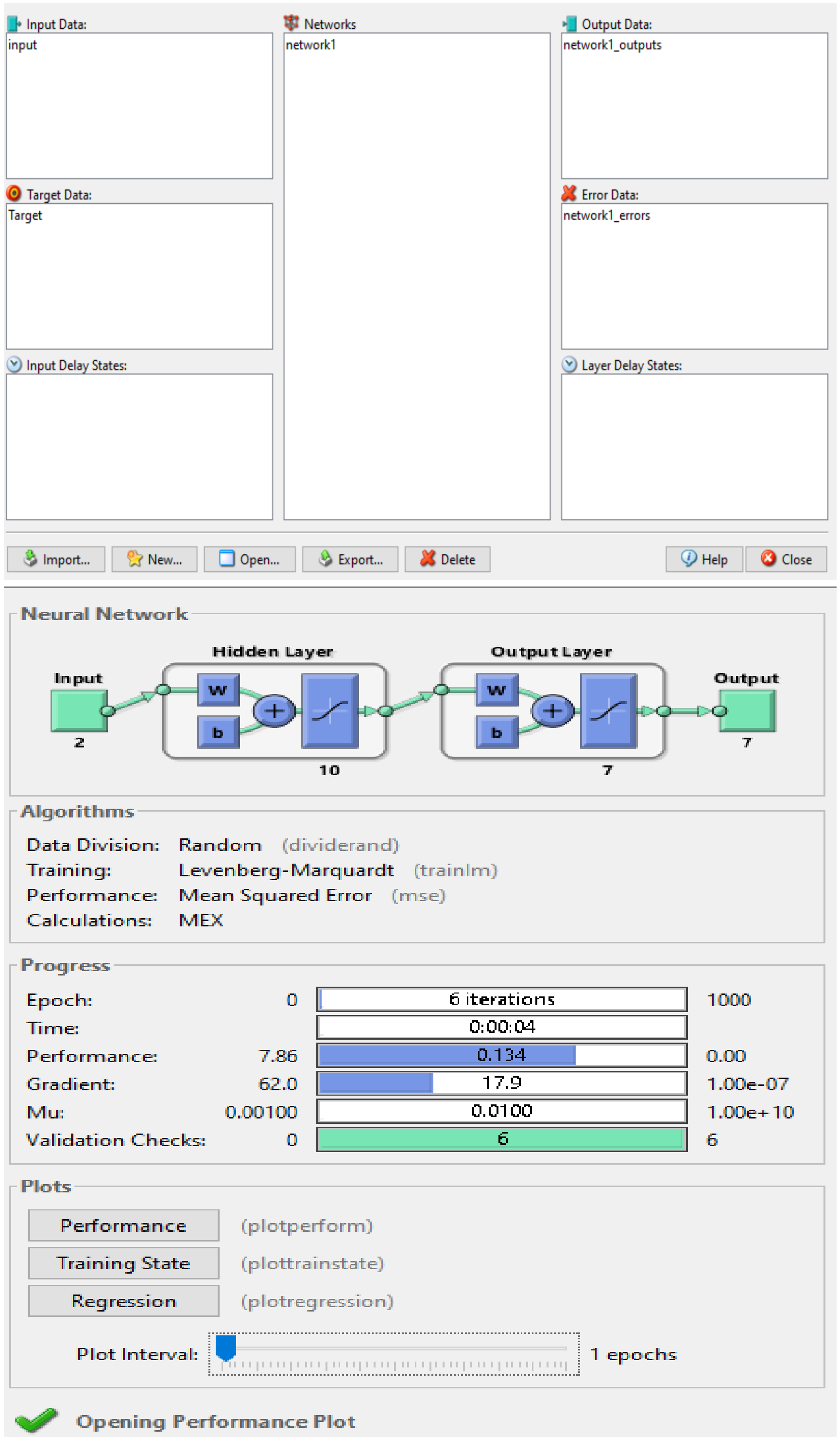
Appendix B: Engine performance results of RSM and ANN

Run	Variables		BT			BP			BSFC		
	load	n-butanol	Actual	RSM	ANN	Actual	RSM	ANN	Actual	RSM	ANN
1	25	10	2.43	2.7649	2.4391	0.60	0.6904	0.5865	0.546	0.5153	0.5236
2	75	30	6.41	6.2380	6.3856	2.29	2.2311	2.3191	0.491	0.4791	0.4513
3	15	20	3.03	2.4047	2.8219	0.49	0.3394	0.4632	0.586	0.6340	0.5597
4	25	20	2.37	2.7238	2.3268	0.58	0.6579	0.5552	0.551	0.5200	0.5662
5	50	20	4.20	4.1212	4.3312	1.49	1.4708	1.5036	0.379	0.3844	0.3756
6	50	20	4.21	4.1212	4.4187	1.50	1.4708	1.5107	0.380	0.3844	0.3623
7	80	20	6.55	6.9292	6.5210	2.37	2.4772	2.3598	0.488	0.5035	0.4991
8	50	0	4.29	4.2471	4.3105	1.58	1.5722	1.5705	0.368	0.3842	0.3483
9	50	20	4.19	4.1212	4.2236	1.48	1.4708	1.4963	0.378	0.3844	0.3725
10	25	30	2.34	2.6563	2.8652	0.55	0.6219	0.5361	0.556	0.5353	0.5889
11	50	10	4.25	4.1973	4.2740	1.55	1.5233	1.5884	0.375	0.3790	0.3684
12	50	30	4.12	4.0187	4.0847	1.42	1.4148	1.4039	0.384	0.4005	0.3809
13	75	10	6.64	6.4866	6.5684	2.42	2.3796	2.4360	0.478	0.4561	0.4811

Appendix C: Engine emissions results of RSM and ANN

Run	Variables		CO_2			NOx			CO			HC		
	load	n-butanol	Actual	RSM	ANN	Actual	RSM	ANN	Actual	RSM	ANN	Actual	RSM	ANN
1	25	10	2.73	2.7153	2.7452	43	47.444	41.5691	0.044	0.042433	0.0419	47	45.00488	48.3297
2	75	30	3.84	3.8437	3.8399	201	201.608	202.5693	0.04	0.040521	0.0354	46	44.12809	47.6954
3	15	20	2.29	2.3159	2.2864	31	29.374	33.4625	0.051	0.053341	0.0519	53	56.00661	51.0028
4	25	20	2.65	2.6406	2.6579	40	42.234	39.9845	0.046	0.04456	0.0476	50	48.9917	52.5310
5	50	20	3.36	3.3569	3.3791	145	142.513	146.4123	0.033	0.033621	0.0329	27	27.93558	26.3349
6	50	20	3.37	3.3569	3.3923	147	142.513	149.7532	0.034	0.033621	0.0350	28	27.93558	28.8680
7	80	20	4.05	4.0366	4.0321	219	219.035	218.6631	0.042	0.041266	0.0414	44	46.08985	45.0199
8	50	0	3.5	3.4979	3.4989	162	161.061	163.3549	0.03	0.030344	0.0290	24	25.96497	22.8865
9	50	20	3.35	3.3569	3.3469	144	142.513	145.2569	0.033	0.033621	0.0330	27	27.93558	27.6392
10	25	30	2.57	2.5523	2.5862	38	37.651	37.8827	0.048	0.047162	0.0488	52	48.98153	54.9850
11	50	10	3.42	3.4342	3.4146	151	149.973	153.1459	0.031	0.031744	0.0309	25	25.94877	24.3498
12	50	30	3.25	3.2661	3.2438	141	140.680	139.0026	0.036	0.035973	0.0366	29	31.92541	27.3692
13	75	10	4.01	4.0167	4.0098	211	213.401	213.8103	0.037	0.036792	0.0363	41	42.15145	40.2443

Appendix D: ANN creation and training



Appendix E: Engine Test Setup

Appendix F: Structural, Chemical and Physical Properties of the n-butanol

Properties	Specifications
Description	Colorless liquid, medium volatility, banana-like odor
Synonyms:	butan-1-ol, 1-butanol, normal butanol, and n-butyl alcohol
Cas Number	71-36-3
Molecular Formula	C_4H9OH
Molecular weight	74.12
Autoignition temperature	343 °C
Flashpoint	29 °C - 35 °C
Melting Point	-90 °C
Boiling Point	117 °C
Density	0.81 kg/m^3 at 20 °C
Vapor Pressure	0.58 kPa at 20 °C