sustainability

Article

Significant Research on Sustainable Oxygenated Fuel for Compression Ignition Engines with Controlled Emissions and Optimum Performance Prediction Using Artificial Neural Network

Javed Syed

Department of Mechanical Engineering, King Khalid University, Abha 61421, Saudi Arabia; jjaffer@kku.edu.sa

Abstract: The present work compares the performance and emissions of a compression ignition (CI) engine using dual-mode LPG at varying flow rates and an oxygenated biodiesel mix (B20). The experimental investigation is carried out on LPG flow rates (0.1, 0.3, and 0.5 kg/h) and replacing the diesel with oxygenated B20, affecting engine performance and emissions under various load circumstances while maintaining engine speed. The study demonstrates the potential of the artificial neural network (ANN) in accurately forecasting the performance and emission characteristics of the engine across different operating conditions. The ANN model's high accuracy in correlating experimental results with predicted outcomes underscores its potential as a dependable instrument for optimizing fuel parameters. The results show that LPG and oxygenated B20 balance engine performance and emissions, making CI engine functionality sustainable. A biodiesel blend containing diethyl ether (B20 + 2%DEE) exhibits slightly reduced brake thermal efficiency (BTE) at lower brake power (BP); however, it demonstrates advantages at higher BP, with diethyl ether contributing to improved ignition quality. The analysis indicates that the average NO_x emissions for B20 + 2%DEE at flow rates of 0.1 kg/h, 0.3 kg/h, and 0.5 kg/h are 29.33%, 28.89%, 48.05%, and 37.48%, respectively. Consequently, selecting appropriate fuel and regulating the LPG flow rate is critical for enhancing thermal efficiency in a dual-fuel engine.

Keywords: oxygenated fuel additive; B20; LPG dual mode; ANN; performance and emissions

check for updates

Academic Editor: Juan Hernández Adrover

Received: 25 December 2024
Revised: 13 January 2025
Accepted: 16 January 2025
Published: 20 January 2025

Citation: Syed, J. Significant Research on Sustainable Oxygenated Fuel for Compression Ignition Engines with Controlled Emissions and Optimum Performance Prediction Using Artificial Neural Network. *Sustainability* **2025**, *17*, 788. https://doi.org/10.3390/su17020788

1. Introduction

The increasing demand for alternative fuels can be attributed to environmental concerns, the necessity to decrease dependence on fossil fuels, and the drive for sustainability within the energy sector. Alternative fuels offer several advantages, including their renewable characteristics and the potential to reduce harmful emissions. Additionally, it is important to consider the geopolitical and regulatory factors that influence their adoption. Advancements in technology have enhanced the feasibility and cost-effectiveness of these fuels; however, greenhouse gas emissions have continued to increase, highlighting an ongoing challenge in addressing climate change [1–5]. Research on alternative fuels, particularly biodiesel, is limited due to a lack of comprehensive studies on their long-term effectiveness in reducing greenhouse gas emissions. Machine learning can enhance engine performance and lower emissions, with studies showing significant reductions in NO_x and smoke emissions at a 30% CNG energy share and a 4.35% increase in thermal efficiency [6].

Researchers study alternative biodiesel fuels, including parsley biodiesel and acetylene gas with microalgae biodiesel. B20 blend enhances engine performance and reduces emissions but increases NO_x. Advanced fuel injection timing also improves performance [7,8]. The experimental investigation on microalgae biodiesel and biofuel blends has shown improved dual-fuel CI engine performance and reduced emissions. While existing studies show improved brake thermal efficiency and reduced CO and HC emissions, NO_x levels are slightly increased. However, a research gap exists in exploring the long-term effects of these biofuels on engine performance and emissions and evaluating predictive models beyond ANN, GBR, and GPR [3,9,10].

Sanjeevannavar et al. [11] tested biodiesel blends with hydrogen peroxide additives in an internal combustion engine, finding XG Boost as the most accurate model for predicting performance and emissions [12,13]. Six artificial neural network models were developed to predict the performance and emissions of a diesel engine operating on 8% biodiesel. The models demonstrated reliable power, efficiency, and emissions predictions across various load conditions, providing a solid foundation for the accuracy of the research. The models exhibited consistent power, efficiency, and emissions predictions under different load conditions, further reinforcing the role of machine learning in predicting engine performance [14]. Awogbemi and Von Kallon [15] analyzed the benefits of biodiesel as a sustainable fuel source, outlining the use of machine learning techniques, including ANN, RSM, and ANFIS, in optimizing production processes, which leads to improved yields and accuracy. Hybrid approaches are crucial in this domain, as advanced hybrid methodologies that integrate machine learning with optimization techniques are increasingly gaining traction. Sharma et al. [16] have optimized dual-fuel engine performance with biodiesel and producer gas using Artificial Neural Networks (ANN) to reduce emissions and improve combustion. The development of a dual-fuel combustion engine utilizing a biodiesel/diesel pilot and producer gas has successfully created a multi-layer perceptron artificial neural network (MLP-ANN) model with a 3–10-6 topology. This model effectively predicted and optimized combustion–emission characteristics, resulting in a significant reduction. For instance, Soudagar et al. [17] studied ANN with Ant Colony Optimization (ACO)-optimized biodiesel production, providing excellent yield predictability. Similarly, Seela et al. [18] developed a Multitarget Regression model for predicting performance and emissions, demonstrating the utility of Multitarget Regression algorithms. Gaussian Process Regression is the most accurate model for predicting diesel engine fuel consumption, outperforming Neural Networks and Random Forest Regression [19–21]. Recent studies show that Deep Neural Networks and MIMO-ANN improve engine testing accuracy and efficiency, reducing experimental efforts. Biodiesel production using non-edible oils and waste feedstocks addresses food security and cost issues. Nanoparticles and chemical additives improve biodiesel properties. Machine learning and Deep Learning predict engine performance and emissions from waste fry biofuel. Kernel-based extreme learning machines assess biodiesel–bioethanol–diesel blends [22–28]. However, combining modern modeling approaches for biodiesel synthesis utilizing non-edible oils and waste feedstocks is still lacking. While various feedstocks have been studied for their environmental and economic advantages, little is known about how DNNs and MIMO-ANNs can optimize engine settings for biodiesel from these alternative sources. The effects of nanoparticles and chemical additives on biodiesel blend performance using machine learning are also unknown. Research might create comprehensive models that include these factors to improve biodiesel's efficiency and sustainability as a diesel replacement.

The analysis shows how biodiesel innovation, machine learning (ML), and optimization tactics provide sustainable engine performance and pollution management. Although progress has been achieved, NO_x emissions and biodiesel manufacturing costs remain significant challenges that require urgent attention in future research. Future research should integrate real-time ML-based monitoring systems and investigate new biofuel compositions to fulfill energy and environmental needs. Researchers are studying alternate IC engine fuels because of environmental concerns, fossil fuel depletion, and the need for sustainable energy. Due to its biodegradability and lower emissions, biomass-based biodiesel may replace diesel. Its high viscosity and low energy density may limit its fuel efficiency. Adding Liquefied Petroleum Gas (LPG) to CI engines may boost combustion efficiency and reduce pollutants. The significance of this research lies in its exploration of advanced machine-learning techniques to enhance the performance of tractors and compression ignition (CI) engines, which are critical in agricultural operations. By employing methods such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), XGBoost, and Deep Learning (DL), the study aims to optimize fuel consumption and reduce harmful emissions, thereby contributing to more efficient and environmentally friendly agricultural practices [29–31].

The dual-fuel approach poses a considerable challenge in optimizing the characteristics of biodiesel blends. This optimization is critical for ensuring compatibility with LPG and enhancing the efficient operation of compression ignition engines. Integrating oxygenated additives to improve the combustion characteristics of biodiesel blends is a viable method. Adding these additives leads to decreased emissions, increased calorific value, and improved ignition quality of the fuel blend. This study aims to investigate the formulation of a biodiesel blend that incorporates an oxygenated additive and evaluate its performance when utilized alongside LPG as a secondary fuel in a compression ignition engine. The objective is to assess the combustion characteristics, engine performance, and emission profile to develop a sustainable and efficient dual-fuel system. To achieve this, biodiesel is produced from waste biomass (from palm trees), i.e., palm kernel methyl ester (PKme). Subsequently, the PKme will be diluted with an oxygenated additive, and the performance emission of the CI engine will be analyzed. Further, experiments with LPG at various flow rates will be conducted. Then, the artificial neural network (ANN) network will be employed to develop a simulation process utilizing an artificial neural network (ANN) to identify the optimal parameters. This analysis utilizes four types of networks, each configured with either a single or double hidden layer comprising 10 hidden neurons.

2. Preparation and Properties of B20 Blend

Producing biodiesel from palm kernel oil entails transesterification, wherein palm kernel oil undergoes a reaction with an alcohol, generally methanol, facilitated by a catalyst, as presented in Figure 1. This reaction yields palm kernel methyl ester (PKme) and glycerol as a byproduct. The initial step involves pre-treating palm kernel oil to eliminate impurities, including free fatty acids and moisture, which may disrupt the reaction. Producing biodiesel from palm kernel oil is initiated by determining the free fatty acid (FFA) content via titration. Oils exhibiting free fatty acid (FFA) levels greater than 3% necessitate a pretreatment process involving acid esterification to lower the FFA concentration to below 3%. This is subsequently followed by alkali esterification. Acid esterification requires heating 750 mL of palm kernel oil (PKO) to a temperature of 45 °C. Subsequently, methanol is added at a ratio of 0.2 vol/vol, along with sulphuric acid (H_2SO_4) at a concentration of 0.7% vol/vol. The mixture is then stirred and maintained at 65 °C for 70 min. After this period, glycerol is separated following a settling time of six hours. The process of alkali esterification involves the following steps: Combine 7.5 g of KOH with methanol at a ratio of 0.2 vol/vol. Heat the oil to a temperature of 45 °C. Subsequently, potassium methoxide was introduced, and the reaction was maintained at 70 °C for one hour. The glycerol and biodiesel layers are separated. The biodiesel is subjected to water washing, consisting of five cycles with distilled water, to eliminate impurities. Subsequently, dehydration is performed at 100 °C to remove any residual water.

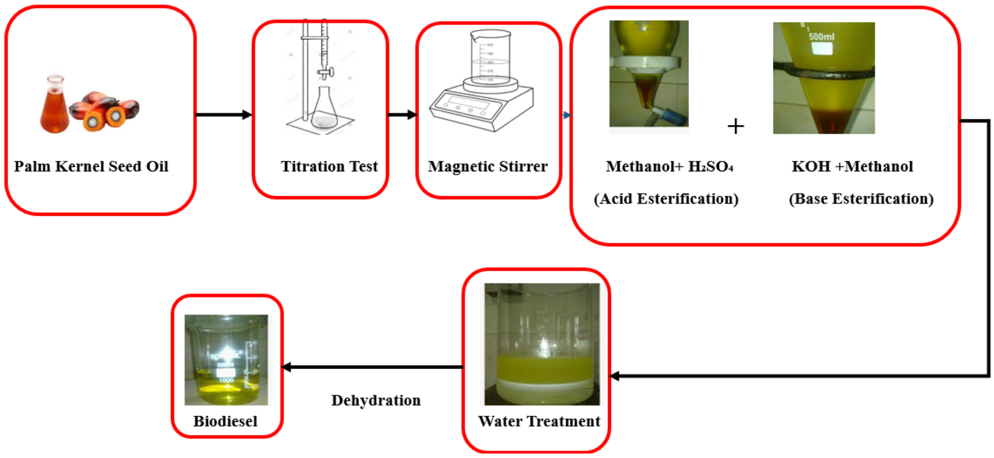


Figure 1. Preparation of PKme biodiesel using the transesterification process.

The flash point is determined for biodiesel characterization using Cleveland's flash fire point apparatus. Viscosity is measured using a Redwood Viscometer, where oil is heated in a water bath and flow time for 50 mL is recorded at various temperatures. Calorific value is assessed using a bomb calorimeter, where 0.81 g of oil is burned in an oxygen-filled bomb inside a water bath. Temperature changes are recorded with a Beckmann thermometer to calculate lower heating values. The process emphasizes critical parameters such as reaction time (1 h), temperature (60 °C ± 2), methanol ratio, and catalyst amounts for optimizing biodiesel yield and quality. The flash point and fire point of PKme fuel are measured at 163 °C and 166 °C, respectively, while its cloud and pour points are recorded at 14.5 °C and 12.5 °C. In this study, the B20 blend, known for its 80% diesel and 20% PKme, is used in the CI engine. Diethyl ether (DEE) is an oxygenated additive and will be added to the B20 blend to prepare fuel for the CI engine. The biodiesel properties were tested using ASTM standards, as shown in Table 1.

Table 1. Properties of PKme, B20 and other fuels.

Parameter/Property	PKme	B20	DEE [32]	Diesel [32]	LPG [32]
Density (kg/m^3)	885	838	713	833	505
Viscosity at 20° (cp)	7.64	5.72	0.23	4.21	-
Calorific value (kJ/kg)	35,008	39,051	33,900	42,500	46,380

3. Methodology

LPG comprises 65% propane and 35% butane. The primary component is propane, characterized by a low carbon-to-hydrogen ratio. Its elevated octane rating and capacity to create a homogeneous mixture within the combustion chamber facilitate reduced emissions compared to traditional fuels. LPG is typically stored in pressure vessels at a pressure of 7 bar, which may vary based on ambient temperature conditions. The diesel engine with electric loading is utilized for experimental purposes. The engine has been modified to accommodate diesel, oxygenated B20, and LPG. In the current study, an oxygenated B20 blend is prepared using 2%DEE, referred from the literature [33]. The initial step involves the entry of LPG into the mixing chamber, where it is combined with fresh atmospheric air. Subsequently, the mixture is directed to the engine via the inlet manifold. The flow control valve installed between the cylinder and the solenoid valve regulates the LPG flow rate. The homogeneous mixture is introduced into the engine via the intake valve, where it undergoes compression in conjunction with the air. A precise volume of B20 + 2%DEE is injected into the cylinder utilizing a fuel injector. Upon achieving the self-ignition condition, the oxygenated B20 fuel within the cylinder initiates the combustion process. The combustion process of LPG occurs with the assistance of the temperature present within the combustion chamber. Figure 2a–c illustrates the schematic diagram of the dual-fuel mode experimental setup and a photograph of the setup. LPG alone cannot self-ignite within a diesel-fuel compression–ignition engine. In the compression stroke, the air and LPG mixture undergoes compression, increasing the temperature to approximately 400 °C. This temperature is insufficient to ignite the LPG, which has an ignition temperature of around 500 °C. Upon atomization of oxygenated B20 fuel into the cylinder at high pressure, self-ignition occurs, leading to the combustion of LPG. Due to the presence of LPG as a mixture with air, the flame front generated by the oxygenated B20 fuel propagates at an accelerated rate and with greater completeness. This includes igniting the air–fuel mixture that comes into contact with the cooler cylinder walls, contrasting with the super-heated air within the combustion chamber.

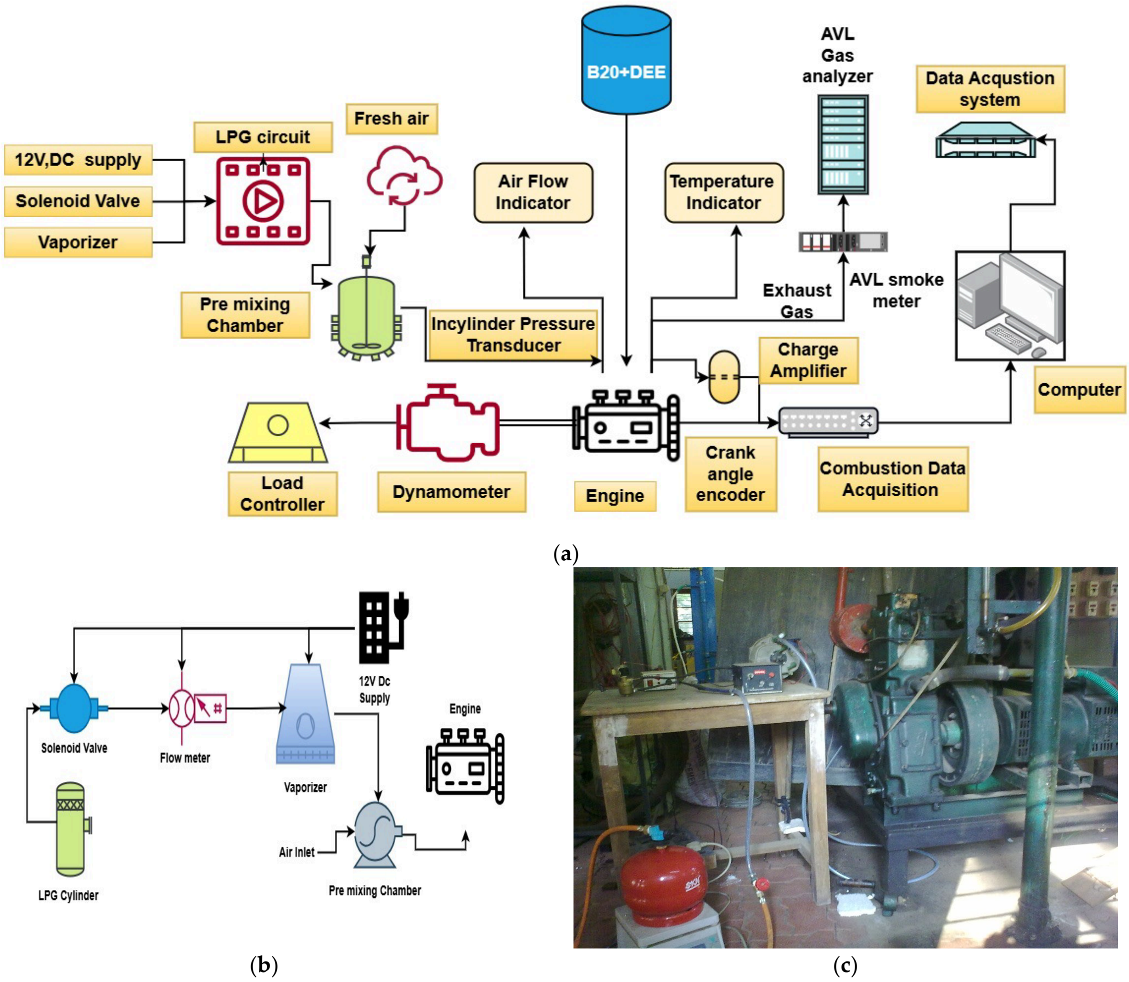


Figure 2. (**a**) Experiment Schematic layout (**b**) LPG supply regulating Circuit (**c**) Modified engine test rig.

Engine tests are conducted with diesel, B20 + 2%DEE and at various percentages of LPG within the air–gas mixture. This investigation introduces LPG with intake air via a premix chamber and uses B20 + 2%DEE as an ignition enhancer instead of diesel. The LPG from the cylinder is combined with ambient air in the mixing chamber. The inlet manifold introduces the premixed fuel-air mixture into the combustion chamber. The flow rate of

LPG to the engine is manually adjusted within a range of 0.1 kg/h to 0.5 kg/h using a flow regulating valve. The engine automatically adjusts the B20 + 2%DEE flow rate to satisfy its energy requirements. Performance and emission tests are conducted at varying LPG flow rates under different load conditions, with the engine operating at a constant speed. The load is adjusted using an electrical loading system. A single-cylinder, water-cooled DI diesel engine (7 hp at 1500 rpm) was used for experiments. Moreover, engine specifications and uncertainties of parameters measured in the experiments are presented in Tables 2 and 3, respectively. LPG flow rates were fixed at 0.1 kg/h, 0.3 kg/h and 0.5 kg/h. Key parameters such as fuel consumption, CO, NO_x, and exhaust gas temperature were recorded.

Table 2. Specifications of the Engine.

Engine type	4-stroke, Single cylinder diesel engine
Rated power	7 hp
Speed	1500 rpm
Stroke	110 mm
Alternator capacity	5 KVA
Orifice diameter	20 mm
Compression ratio	16.5
Cooling	Water cooling type

Table 3. Uncertainty of parameters measured in the experiments.

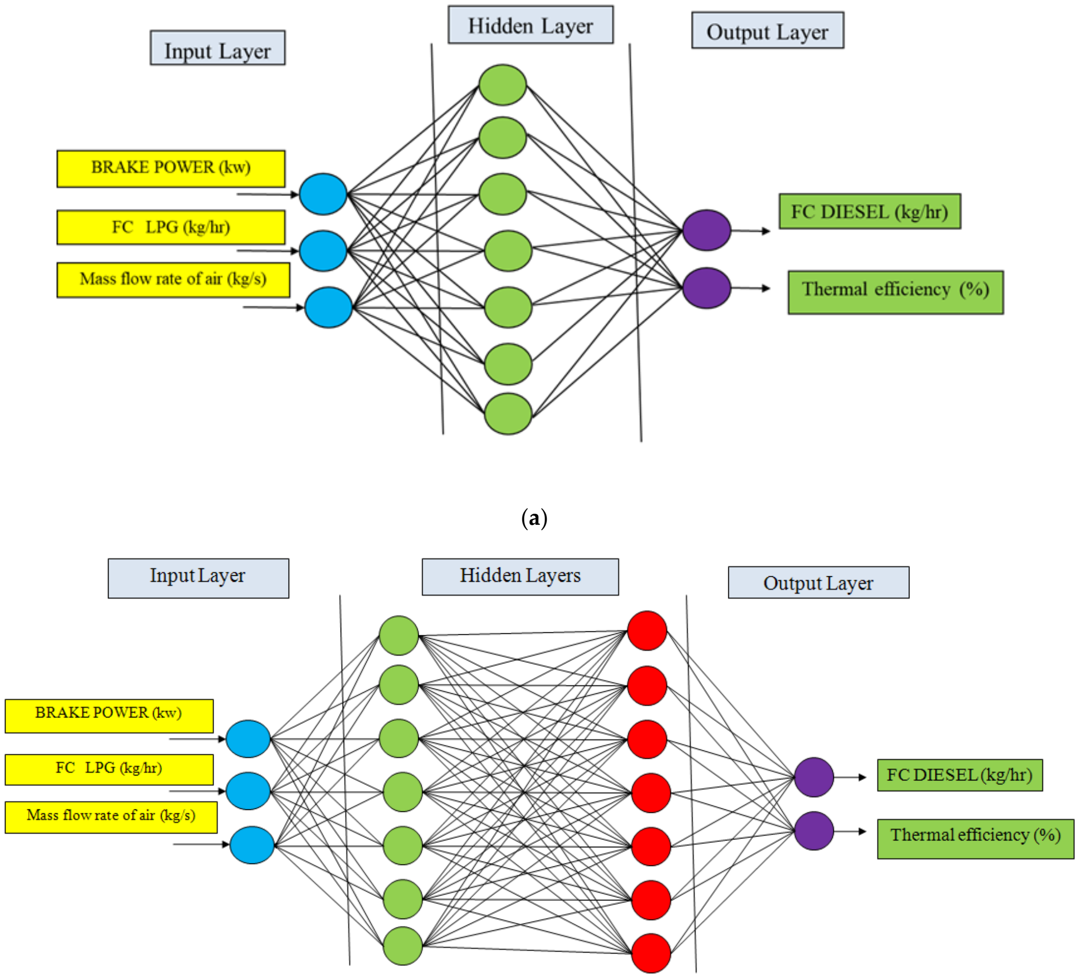
Parameter	**Uncertainty**
Time (Sec)	±0.5
Fuel consumption (kg/h) for diesel, B20	±0.0057
Fuel consumption (kg/h) for LPG	±0.011045
Sp. Energy consumption (MJ/kW h)	±0.05479
η_{BTE} (%)	±0.853
η_{ITE} (%)	±0.853
Temperature (°C)	±0.15% of reading
Emission (CO, CO_2, NO_x & HC) in ppm	Both CO & CO_2 ±2.5% of reading, NO_x is ±5, HC is ±6,

4. ANN Modeling

Artificial Neural Networks (ANNs) are structured data processing systems comprising input, hidden, and output layers, which can be either feed-forward or recurrent. Their configuration and training methods influence their performance, including learning from labeled data, unsupervised learning, or reinforcement learning. A key training method is the backpropagation algorithm, and performance is evaluated using metrics like sum squared and mean squared errors. ANNs are particularly important for modeling and predicting engine performance in complex, non-linear systems, as they can be effective. ANNs enhance accuracy by adapting to empirical data, making them applicable across various engine configurations. This adaptability is essential for optimizing engine performance and developing more efficient, environmentally friendly combustion systems.

For a dual-mode LPG-operated compression ignition (CI) engine, backward Neural Networks offer immense research potential in optimizing performance, emissions, and fuel efficiency. Such engines operate under dual-fuel conditions, typically combining LPG with a small quantity of pilot diesel for ignition. Backward Neural Networks can model complex combustion dynamics, including fuel-air mixing, ignition delay, and flame propagation, by leveraging the backpropagation mechanism to learn patterns from experimental data. These models can help optimize LPG substitution ratios, predict NOx and particulate emissions, and enhance thermal efficiency. Additionally, they can facilitate adaptive control strategies by integrating real-time sensor data, enabling precise adjustments to fuel injection timing, pressure, and air-fuel ratios, ultimately improving engine performance while minimizing environmental impact.

The ANN prediction tool was utilized to forecast the output values across all ranges. Modeling procedures are utilized to predict the system's outcome without conducting real-time experiments. Various modeling procedures exist for calculating future output based on current and historical input-output signals. The importance of this concept in engineering has facilitated numerous parametric and non-parametric modeling techniques across various thrust areas. This analysis focuses on artificial neural systems that configure frameworks composed of neurons to address complex problems, aiming to replicate the structure and function of biological neurons. A neural system framework consists of three distinct layers: the input, hidden, and output. The network configuration of the ANN model for the LPG-fueled CI engine is illustrated in Figure 3 for both single and double hidden layers, with specifications. The perception network in MATLAB 2019 software was utilized to adjust the synaptic weights automatically. The regression value obtained in this study ranged from 0.95 to 1.



(**a**) (**b**)

Figure 3. ANN configuration (**a**) Single hidden layer (**b**) Double hidden layer.

The Purelin function is utilized for hidden and output neurons, while the Transig transfer function is typically employed between input and hidden neurons. Figure 4 illustrates the flow chart outlining the development and training process of the ANN model utilized for the performance prediction of a dual-fuel engine. The ANN utilized for performance prediction was developed within the MATLAB environment, employing the neural network toolbox. A total of 10 neurons were utilized in the hidden layer during the training process. The backpropagation algorithm, the most commonly utilized method in ANN, optimizes weight connections by enabling the error to propagate from the output layers to the lower layers, including the hidden and input layers.

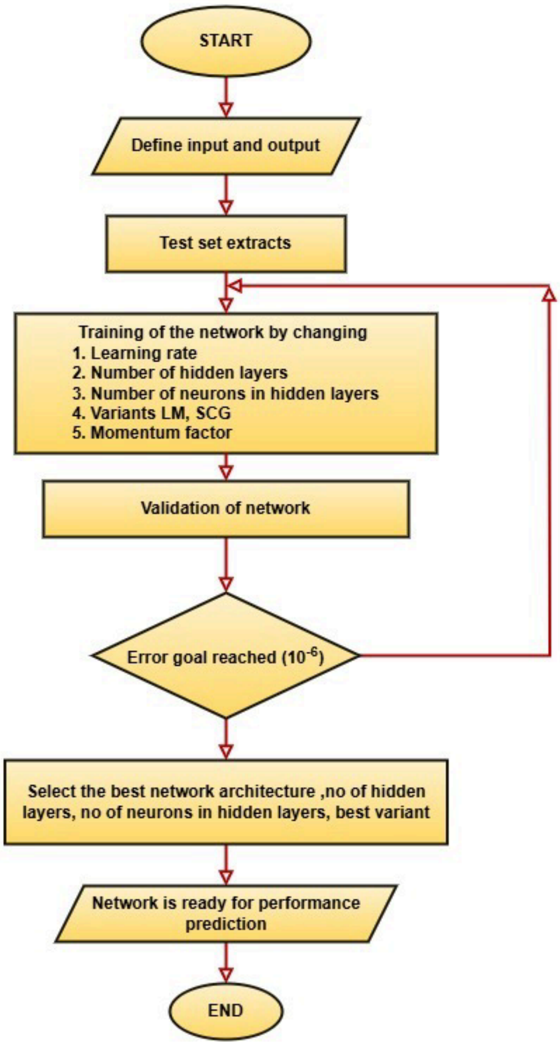


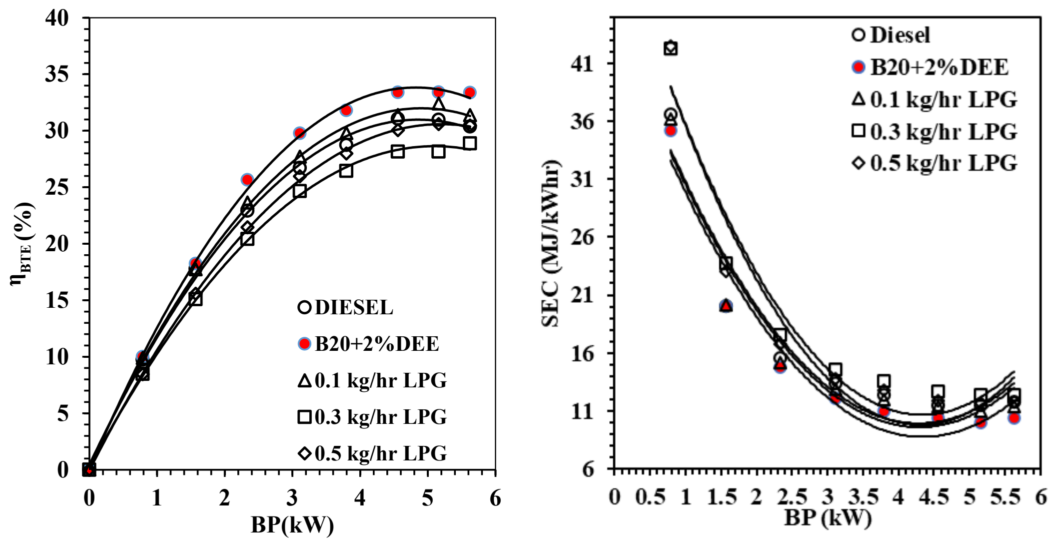
Figure 4. ANN modeling workflow.

The network's output is evaluated against the desired output during each presentation, and errors are calculated accordingly. The errors were subsequently backpropagated to the ANN to adjust the weights, reducing errors with each iteration and enabling the ANN model to approximate the desired output more accurately. The network training continues until the specified error goal of 10^{-6} is reached. The current study employs the backpropagation algorithm in conjunction with a variant of the Levenberg–Marquardt method. The predicted results from the ANN are compared with the actual experimental results to assess the network's performance. The optimal network architecture was determined based on the network's performance results. This method is selected to predict the performance of a dual-fuel engine. One method for identifying a suitable substitute for diesel involves conducting experiments in an internal combustion engine operating in dual-fuel mode with LPG to determine the optimal blend performance of the engine. Given that experimentation requires significant time and financial resources, it is essential to consider alternative methods. A simulation model is developed using ANN to predict the performance of a compression ignition (CI) engine operating in dual-fuel mode.

5. Results and Discussion

5.1. Performance Comparison

A dual-fuel engine's brake thermal efficiency (BTE) varies significantly depending on the fuel type and brake power (BP). BTE is generally higher for diesel at lower BP and shows a gradual increase with increasing BP due to improved combustion efficiency, as shown in Figure 5a. B20 + 2%DEE (biodiesel blend with diethyl ether), BTE tends to be slightly lower compared to diesel at lower BP but improves as BP increases, owing to better ignition quality provided by DEE. When LPG is introduced at varying flow rates (0.1, 0.3, and 0.5 kg/h), the BTE generally decreases compared to diesel, especially at lower BP. This is because LPG has a lower cetane number, leading to delayed combustion. However, the dual-fuel operation can show improved BTE at higher BP due to enhanced mixing and combustion characteristics. The BTE decreases as the LPG flow rate increases from 0.1 to 0.5 kg/h, indicating that excessive LPG substitution can reduce the combustion efficiency. The choice of fuel and LPG flow rate profoundly impacts the engine's thermal efficiency across different operating conditions. The analysis predicts the brake thermal efficiency of 8.01%, 2.7%, 9.8%, and 5.3% for B20 + 2%DEE, LPG at 0.1 kg/h, 0.3 kg/h, and 0.5 kg/h, respectively, in comparison to diesel fuel.



(**a**) (**b**)

Figure 5. Comparison of (**a**) Brake thermal efficiency and (**b**) Specific Energy Consumption (SEC).

A dual-fuel engine's specific energy consumption (SEC) varies with fuel type, LPG flow rate, and brake power. SEC typically decreases as BP increases for diesel due to better fuel utilization and reduced relative heat losses at higher power outputs. Diesel demonstrates the lowest SEC compared to other fuel combinations, indicating efficient energy conversion. In the case of B20 + 2%DEE, SEC is slightly higher than diesel at low BP because of the lower energy content of the biodiesel blend, as shown in Figure 5b. However, the oxygen content in DEE improves combustion at higher BP, reducing SEC closer to diesel levels. SEC increases when LPG is introduced at 0.1, 0.3, and 0.5 kg/h compared to diesel, especially at higher flow rates. At 0.1 kg/h, the SEC is relatively close to diesel, as a small amount of LPG enhances combustion efficiency. SEC rises as the flow rate increases to 0.3 and 0.5 kg/h due to incomplete combustion and energy losses caused by excessive LPG substitution. The trend indicates that optimized LPG flow rates are crucial to achieving reasonable SEC in dual-fuel engines, particularly at varying power outputs.

The diesel replacement rate in a dual-fuel engine, a key factor in reducing fossil diesel dependency, can be significantly improved with the introduction of LPG or a biodiesel blend, as shown in Figure 6a. For B20 + 2%DEE, the diesel replacement is approximately 20%, corresponding to the biodiesel content in the blend. This reduction in fossil diesel dependency does not compromise engine performance, especially at higher BP, where combustion improves. When LPG is introduced at varying flow rates (0.1, 0.3, and 0.5 kg/h), the diesel replacement rate increases proportionally with the LPG flow. At 0.1 kg/h, diesel replacement is moderate, and combustion remains stable. At 0.3 kg/h, the diesel replacement is more significant, with LPG contributing a greater share of the energy input. At 0.3 kg/h, diesel replacement reaches its highest level, but excessive LPG can lead to incomplete combustion or misfires, particularly at lower BP. However, with proper optimization of the LPG flow rate, we can ensure maximum diesel replacement while maintaining engine efficiency and minimizing emissions, paving the way for improved engine performance in the future.

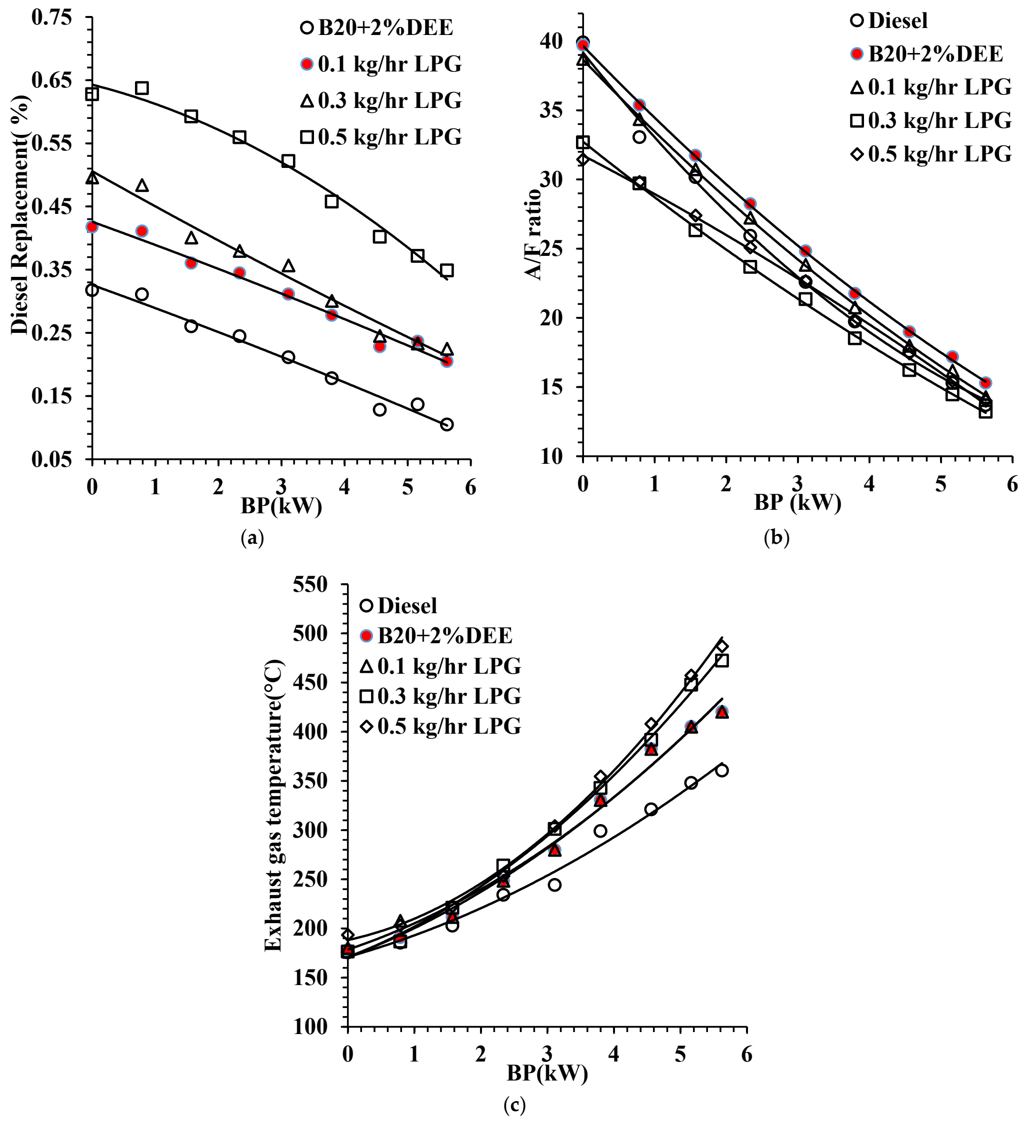


Figure 6. Variation of (**a**) Diesel Replacement (DR) and (**b**) A/F ratio (**c**) Exhaust gas temperature.

A dual-fuel engine's air-fuel ratio (AFR) exhibits distinct variations based on fuel type, LPG flow rate, and brake power (BP). For diesel, the AFR tends to decrease as BP increases since more fuel is injected to meet the higher energy demands, leading to a relatively richer mixture, as shown in Figure 6b. For B20 + 2%DEE, the AFR is generally lower than diesel at low BP due to the higher fuel mass flow rate required for biodiesel blends with lower calorific value. However, the oxygen content in DEE aids combustion, maintaining a relatively stable AFR as BP increases. When LPG is introduced at different flow rates (0.1, 0.3, and 0.5 kg/h), the AFR increases compared to diesel, particularly at higher flow rates. LPG's gaseous nature and lower density contribute to a leaner mixture. The AFR remains near diesel at 0.1 kg/h LPG, ensuring better combustion. However, at 0.3 and 0.5 kg/h, the AFR rises significantly, potentially leading to lean misfires and incomplete combustion at higher BP. Thus, the proper control of the LPG flow rate is not just a technical detail but a crucial aspect of maintaining an optimal AFR across varying BP levels for efficient dual-fuel engine performance.

Exhaust gas temperature (EGT) typically increases with BP for diesel due to higher fuel injection and combustion temperatures as the engine load rises, as presented in Figure 6c. For B20 + 2%DEE, the EGT is slightly higher than diesel at lower BP because of the oxygen content in biodiesel and diethyl ether (DEE), which enhances combustion. At higher BP, the EGT for B20 + 2%DEE approaches that of diesel due to better fuel utilization and reduced heat loss. When LPG is added at different flow rates (0.1, 0.3, and 0.5 kg/h), the EGT trends vary. At 0.1 kg/h LPG, the EGT is comparable to diesel as the additional gaseous fuel improves combustion. At 0.3 kg/h, EGT increases slightly due to enhanced combustion efficiency at moderate LPG flow. However, at 0.5 kg/h, the EGT may decrease at higher BP because of incomplete combustion and excessive air dilution. This highlights the need to optimize LPG flow rates to maintain stable EGT levels and efficient energy utilization across different BP ranges.

5.2. Comparison of Emissions

Nitrogen oxide (NOx) emissions in a dual-fuel engine are influenced by combustion temperature, oxygen availability, and the type of fuel used. For diesel, NOx emissions typically increase with BP due to higher combustion temperatures and increased oxygen availability from air intake, as shown in Figure 7. In the case of B20 + 2%DEE, NOx emissions are generally higher than diesel, especially at lower BP. This is because the oxygen content in biodiesel and DEE enhances combustion, leading to higher in-cylinder temperatures. However, at higher BP, the difference in NOx emissions between diesel and B20 + 2%DEE decreases as the combustion process stabilizes. When LPG is introduced at varying flow rates (0.1, 0.3, and 0.5 kg/h), NOx emissions show a complex trend. At 0.1 kg/h LPG, NOx emissions may slightly increase compared to diesel due to improved combustion efficiency. At 0.3 kg/h, NOx emissions could be further elevated due to higher combustion temperatures caused by enhanced fuel mixing. However, NOx emissions may be reduced by 0.3 kg/h, especially at higher BP, because the leaner air-fuel mixture and lower combustion temperature suppress NOx formation. Thus, the need to optimize LPG flow rates to maintain stable EGT levels and efficient energy utilization across different BP ranges is crucial. It is not just about emissions but about balancing NOx emissions and engine performance, and your role in achieving this balance is significant.

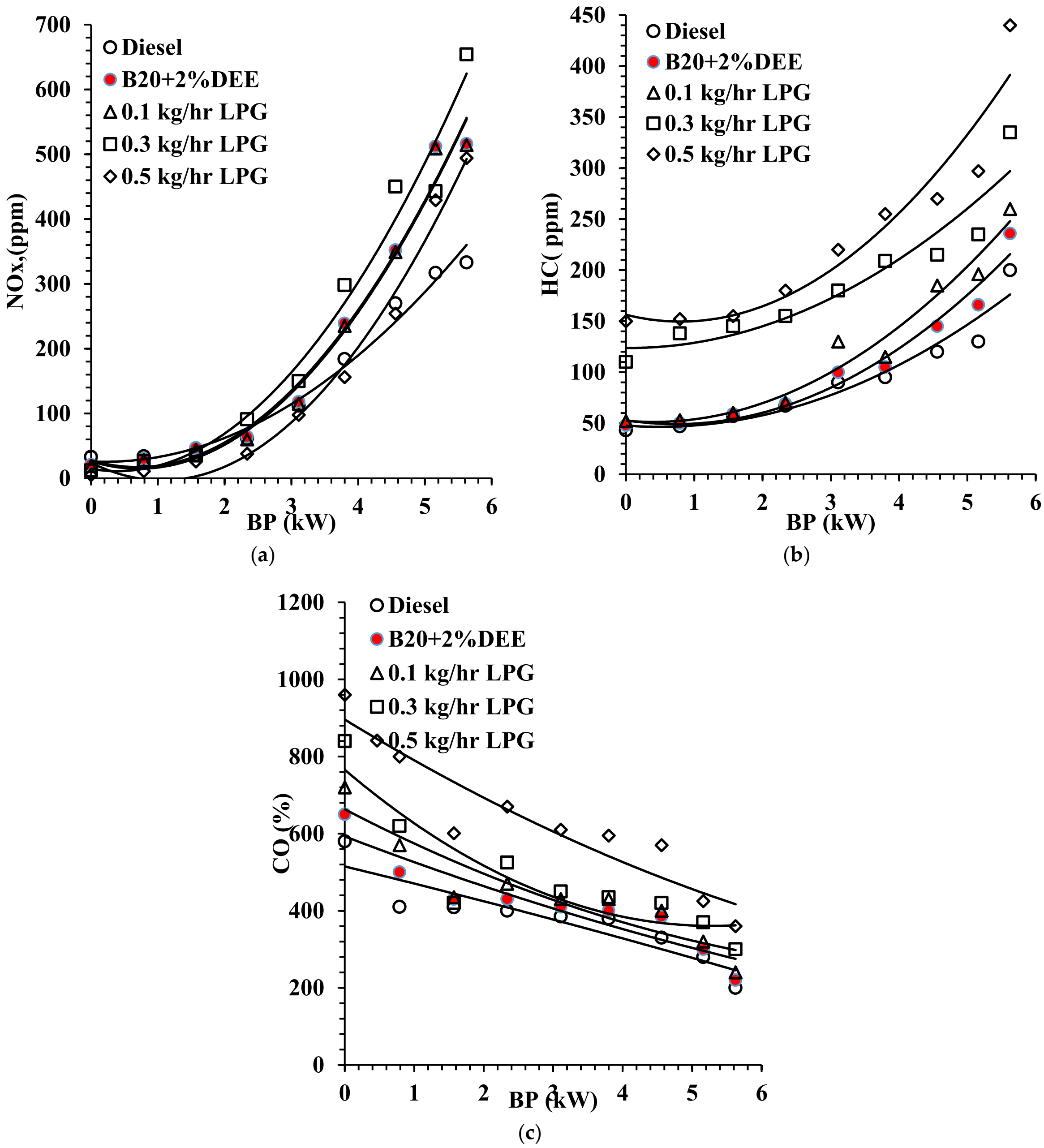


Figure 7. Variation of emissions (**a**) NO_x (**b**) HC (**c**) CO.

A comparison of Hydrocarbon (HC) emissions from CI engines when operating with different fuels is presented in Figure 7a. HC emissions in a dual-fuel engine are affected by combustion quality, fuel type, and LPG flow rate across varying BP levels. The elevated cetane number and optimized combustion process contribute to diesel fuel's generally low HC emissions. However, they may increase slightly at very low BP due to incomplete combustion under light load conditions. For B20 + 2%DEE, HC emissions are generally higher than diesel at low BP due to the lower volatility of biodiesel and its tendency for incomplete combustion. At higher BP, the oxygen content in DEE improves combustion, reducing HC emissions closer to diesel levels. HC emissions increase when LPG is introduced compared to diesel, particularly at higher LPG flow rates. HC emissions remain relatively low at 0.1 kg/h LPG because of better mixing and improved combustion. At 0.3 kg/h, HC emissions may rise slightly due to incomplete combustion of the gaseous LPG. HC emissions significantly increase at 0.5 kg/h, especially at lower BP, as the higher LPG substitution rate leads to fuel-rich pockets and incomplete burning. This highlights the importance of optimizing LPG flow rates to minimize HC emissions across various operating conditions. The intrinsic oxygen in their molecular composition guarantees a more thorough burning of hydrocarbons, even under less-than-ideal combustion circumstances. This leads to little unburned hydrocarbons being released as emissions. More HC emissions are reduced with oxygenated B20 fuel than diesel and dual-mode engines.

The quality of the air-fuel mixture, combustion efficiency, and the type of fuel utilized significantly affect carbon monoxide (CO) emissions in a dual-fuel engine. For diesel, CO emissions are generally low due to the lean combustion process and high combustion temperatures, though they can increase slightly at low BP due to incomplete combustion under light load. For B20 + 2%DEE, CO emissions are typically higher than diesel at lower BP because of the lower volatility of biodiesel and its tendency for incomplete burning. However, at higher BP, the oxygen content in DEE enhances combustion, reducing CO emissions to levels closer to diesel, as shown in Figure 7b. CO emissions show varying trends when LPG is introduced at flow rates of 0.1, 0.3, and 0.5 kg/h, as depicted in Figure 7c. At 0.1 kg/h, CO emissions remain relatively low as the additional gaseous fuel is efficiently combusted. At 0.3 kg/h, CO emissions may increase slightly due to incomplete combustion of LPG in certain operating conditions. CO emissions rise significantly at 0.5 kg/h, particularly at lower BP, as the richer air-fuel mixture and potential misfires contribute to incomplete combustion. Effective control of LPG flow rates is critical to maintaining low CO emissions while achieving optimal engine performance. Moreover, CO emissions are very low when oxygenated fuel is replaced with diesel as a primary fuel in dual-mode engines. The average CO emissions are 10.2%, 18.6%, 30.1%, and 66.01% for B20 + 2%DEE, dual mode LPG with B20 + 2%DEE with 0.1 kg/h, 0.3 kg/h, and 0.5 kg/h, respectively, compared to diesel.

5.3. Performance Prediction Using ANN

The experimental data collected from a series of experiments performed on a dual-fuel compression ignition engine at various mass flow rates of LPG were utilized to train the network. The architecture consists of several layers of neurons, each utilizing non-linear transfer functions, enabling the network to effectively learn non-linear and linear relationships between input and output vectors. The input layer in this study comprises three vector elements: BP, fuel consumption of LPG (FCLPG), and mass flow rate of air (MA). The backpropagation learning algorithm is utilized to train the network. A single hidden layer utilizing the 'tansig' transfer function has been selected for this network configuration. The 'purelin' transfer function is implemented in the output layer, where the output vector element represents the predicted fuel consumption of oxygenated fuel and brake thermal efficiency. The network is initially trained using the specified number of neurons, momentum correction factor, learning rate, and activation function. The network undergoes training until the specified error goal is reached. The network undergoes validation by utilizing the validation data set as input. The predicted outputs, specifically fuel consumption of B20 + 2%DEE and brake thermal efficiency, are then compared against the actual values. In cases where there is a significant discrepancy between the predicted and actual values, the network undergoes a retraining process. The network is trained and validated by adjusting the number of neurons, momentum correction factor, learning rate, and activation function until reliable results are achieved.

Four types of networks are chosen to predict the performance of dual-fuel engines. They are (a) ANN with a single hidden layer using Levenberg–Marquardt (LM) Algorithm, (b) ANN with a single hidden layer using the Scaled Conjugate Gradient (SCG) Algorithm, (c) ANN with a double hidden layer using Levenberg–Marquardt (LM) Algorithm and (d) ANN with double hidden layer using Scaled Conjugate Gradient (SCG) Algorithm. To develop this network, a total of 50 data sets were utilized, with each data set comprising three input variables and two output neurons. The inputs consist of brake power (BP), fuel consumption of LPG (FCLPG), and mass flow rate of air (MA). The outputs include oxygenated B20 fuel consumption (FCD) and brake thermal efficiency (BTH). These ANN models may substantially improve engine performance forecasts and efficiency assessments. The evaluation of ANN designs (single vs. many hidden layers) will ascertain the optimal model. The outcomes of applying the aforementioned two algorithms are evaluated against the experimental results, which involves evaluating different ANN designs, specifically comparing single hidden layer models to those with multiple hidden layers, to determine which configuration provides the best performance in forecasting.

Figure 8 compares the brake thermal efficiency predicted by ANN and the experimentally determined brake thermal efficiency utilizing a single hidden layer. The brake thermal efficiency of the artificial neural network employing a single hidden layer with the Levenberg–Marquardt algorithm demonstrates superior performance compared to the scaled conjugate gradient algorithm. The brake thermal efficiency exhibits a non-linear rise with braking power throughout all graphs, starting from zero and stabilizing between 0.3% and 0.35%. LMD and LMS models often exhibit superior alignment with experimental data relative to SCGD and SCGS, especially at elevated power levels. SCGS routinely underestimates the efficiency seen in Figure 8a. SCGD exhibits more discrepancies from experimental findings at reduced power levels in Figure 8b,c. The models (LMD and LMS) can accurately forecast brake thermal efficiency within the examined range of braking power. Additional tuning may be required for the SCGS and SCGD models to enhance precision, especially in the lower and mid-braking power levels. The experimental data in Figure 8 serve as the standard for assessing model performance. The LMD and LMS models closely correspond with the experimental data, indicating greater precision and less residual error. The SCGD and SCGS models exhibit significant discrepancies, especially at lower and mid-brake power levels, suggesting a possible systematic underprediction. A statistical investigation of residuals (the differences between experimental and model-predicted values) may elucidate whether mistakes are random or systematic, indicating the need for structural enhancements in the model.

The brake thermal efficiency of the artificial neural network (ANN) utilizing a double hidden layer with the Levenberg–Marquardt (LM) algorithm demonstrates superior performance compared to the scaled conjugate gradient (SCG) algorithm. Table 4 presents the errors associated with various Artificial Neural Networks (ANNs), indicating that the Levenberg–Marquardt (LM) algorithm with a double hidden layer results in a lower error rate. The network configuration featuring a linear model with ten neurons in the hidden layer and a double hidden layer demonstrated optimal performance.

The outcomes of applying the aforementioned two algorithms are evaluated against the experimental results. Figure 9 compares the fuel consumption predicted by ANN and the experimentally measured B20 + 2%DEE (oxygenated B20 fuel) consumption, utilizing a single hidden layer. The fuel consumption of the ANN utilizing a single hidden layer with the Levenberg–Marquardt (LM) algorithm demonstrates superior performance compared to the Scaled Conjugate Gradient (SCG) algorithm. The errors related to all Artificial Neural Networks (ANNs) are presented in Table 4, with the Levenberg–Marquardt (LM) algorithm utilizing a double hidden layer demonstrating a lower error rate. The brake thermal efficiency and fuel consumption of diesel (FCD) achieved by the artificial neural network utilizing a double hidden layer with the Levenberg–Marquardt algorithm demonstrates superior performance compared to the scaled conjugate gradient algorithm. This study identified a neural network model with ten neurons in the hidden layer and a double hidden layer as an effective method for predicting the performance of a dual-fuel compression ignition engine.

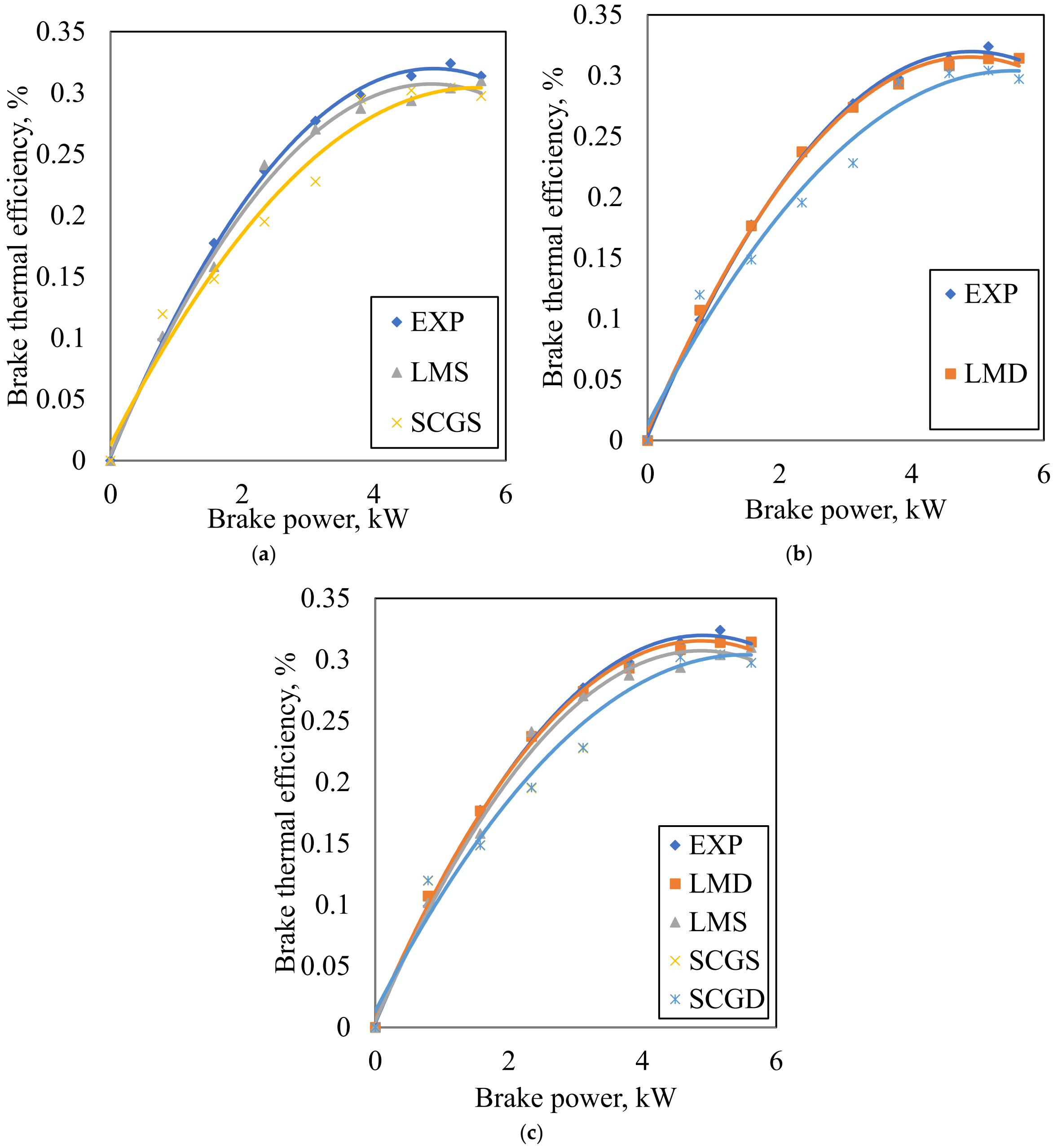


Figure 8. A comparison of ANN-predicted brake thermal efficiency was obtained (**a**) with a single hidden layer, (**b**) with a double hidden layer, and (**c**) with single and double hidden layers.

Table 4. Comparison of errors of various ANN models.

S.No	FC of B20 + 2%DEE				Brake Thermal Efficiency			
	LM		SCG		LM		SCG	
	Single	Double	Single	Double	Single	Double	Single	Double
1.	0.011	0.0187	0.0473	0.0465	0	0	0	0
2.	−0.0004	−0.0057	0.0248	0.0219	−0.0027	−0.0056	−0.0206	−0.0209
3.	−0.0226	−0.001	−0.1058	−0.1128	0.0192	−0.0185	0.0291	0.0286

Table 4. *Cont.*

S.No	FC of B20 + 2%DEE				Brake Thermal Efficiency			
	LM		SCG		LM		SCG	
	Single	Double	Single	Double	Single	Double	Single	Double
4.	−0.0088	−0.0089	−0.049	−0.0562	−0.0049	0.0039	0.0415	0.0408
5.	−0.0145	−0.0115	0.0819	0.0763	0.0067	−0.0038	0.0494	0.0489
6.	−0.0712	−0.0211	0.2239	0.2208	0.0107	−0.0059	0.0031	0.003
7.	−0.085	0.0206	0.1258	0.1215	0.0203	−0.0147	0.0118	0.0118
8.	−0.019	−0.017	0.027	0.028	0.0201	−0.0102	0.0197	0.0198
9.	−0.011	−0.048	0.144	0.146	0.0039	−0.0046	0.0163	0.0164

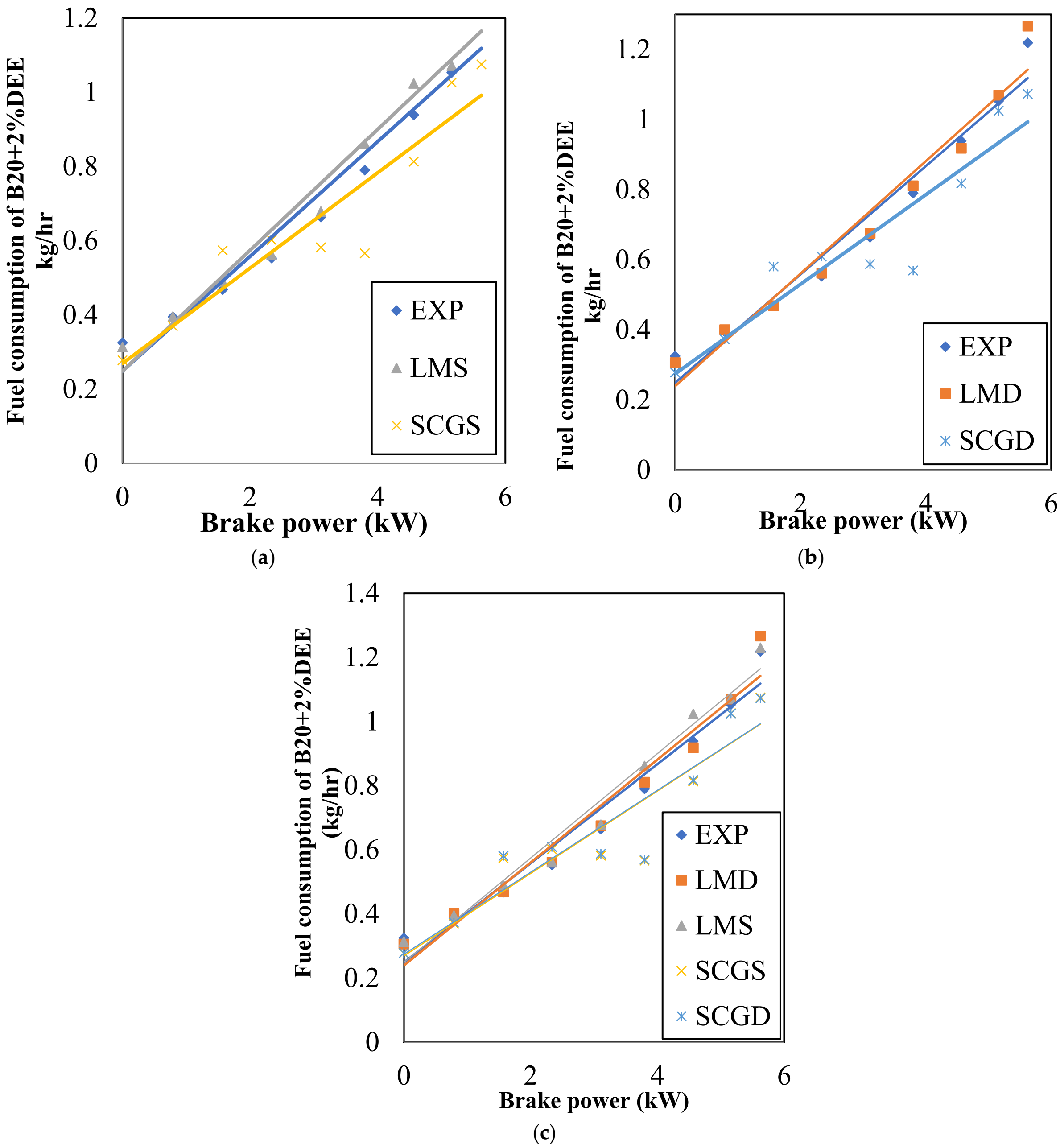


Figure 9. Comparison of ANN predicted fuel consumption (**a**) with single hidden layer (**b**) with double hidden layer (**c**) with single and double hidden layers.

6. Conclusions

The study evaluates a CI engine using liquefied petroleum gas (LPG) and an oxygenated biodiesel blend (B20). It finds that LPG and oxygenated B20 balance engine performance and emissions, making it a sustainable option for CI engine functionality. LPG, a low-carbon-to-hydrogen fuel, is used in a diesel engine for experimental purposes. The engine is modified to accommodate diesel, oxygenated B20, and LPG. An oxygenated B20 blend is prepared using 2%DEE, and the mixture is introduced into the engine. Engine tests are conducted with diesel, B20 + 2%DEE, and various percentages of LPG in the air–gas mixture. The engine adjusts the flow rate to meet energy requirements. Key parameters like fuel consumption, CO, NOx, and exhaust gas temperature are recorded. ANN is employed to predict the performance of a dual-fuel compression ignition engine using experimental data collected at various LPG mass flow rates. The network employs a backpropagation learning algorithm, with a single hidden layer using the 'tansig' transfer function and a 'purelin' transfer function in the output layer, which predicts fuel consumption and brake thermal efficiency.

The introduction of LPG results in decreased BTE, especially at lower BP, due to its lower cetane number, although higher BP can enhance combustion characteristics. However, increasing LPG flow rates can further diminish BTE, highlighting the importance of fuel selection and flow rates on engine thermal efficiency. The predicted BTE values for different fuel combinations demonstrate the varying impacts of these factors on engine performance. LPG at varying flow rates presents a complex relationship with NOx emissions, where lower flow rates may slightly increase emissions, while higher rates can lead to reductions at elevated brake power due to leaner mixtures. Thus, careful management of LPG flow rates is essential for optimizing NOx emissions and overall engine performance, with average NOx emissions recorded at various LPG flow rates indicating significant variability. Biodiesel blends like B20 + 2%DEE have higher HC and CO emissions at low BP due to enhanced oxygen content, while LPG increases HC emissions at higher flow rates. Optimizing fuel mixtures and combustion conditions is crucial for emission reduction and engine performance. Oxygenated fuels like B20 show cleaner combustion potential.

The study uses experimental data from a dual-fuel compression ignition engine to train a network using multiple layers of neurons. The input layer includes brake power, fuel consumption, and air mass flow rate. Four types of Artificial Neural Networks (ANN) are used to predict engine performance, with 50 data sets used. The optimal model is evaluated based on the results, comparing single and multiple hidden layers. The ANN with a single hidden layer and the Levenberg–Marquardt algorithm performs better than the scaled conjugate gradient algorithm. The model can accurately forecast brake thermal efficiency, but additional tuning may be needed for precision.

Funding: This research was funded by Deanship of Research and Graduate Studies at King Khalid University grant number (RGP2/386/45).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through the Large Research Project under grant number RGP2/386/45.

Conflicts of Interest: The author declares no conflict of interest.

Nomenclature

Nomenclature	
A/F ratio	Air-fuel ratio
CO	Carbon monoxide
CO_2	Carbon dioxide
NOx	Nitrogen oxides
HC	Hydrocarbon
hp	Horsepower
SEC	Specific energy consumption (MJ/kWh)
KOH	Potassium hydroxide
H_2SO_4	Sulfuric acid
Abbreviations	
ANN	Artificial neural network
LPG	Liquefied petroleum gas
CI	Compression–ignition
B20	A blend of 20% biodiesel
DEE	Diethyl ether
PKme	Palm kernel methyl ester
CNG	Compressed Natural Gas
GBR	Gradient Boost Regressor
GPR	Gaussian Process Regression
RSM	Root Mean Square
ANFIS	Adaptive network-based fuzzy inference system
ML	Machine learning
DE	Diesel replacement
EXP	Experimental
LMS	Least mean-square
SCGS	Stochastic Conjugate Gradient Strategy
SCGD	Stochastic Conjugate Gradient Descent
LM	Levenberg–Marquardt
PKO	Palm kernel oil

References

1. Sivaranjani, R.; Veerathai, S.; Jeoly Jenifer, K.; Sowmiya, K.; Rupesh, K.J.; Sudalai, S.; Arumugam, A. A Comprehensive Review on Biohydrogen Production Pilot Scale Reactor Technologies: Sustainable Development and Future Prospects. *Int. J. Hydrogen Energy* **2023**, *48*, 23785–23820. [CrossRef]
2. Walker, S.; Rothman, R. Life Cycle Assessment of Bio-Based and Fossil-Based Plastic: A Review. *J. Clean. Prod.* **2020**, *261*, 121158. [CrossRef]
3. Veza, I.; Spraggon, M.; Fattah, I.M.R.; Idris, M. Response Surface Methodology (RSM) for Optimizing Engine Performance and Emissions Fueled with Biofuel: Review of RSM for Sustainability Energy Transition. *Results Eng.* **2023**, *18*, 101213. [CrossRef]
4. Maroušek, J.; Strunecký, O.; Bartoš, V.; Vochozka, M. Revisiting Competitiveness of Hydrogen and Algae Biodiesel. *Fuel* **2022**, *328*, 125317. [CrossRef]
5. Zhu, Y.; Tong, Q.; Yan, X.; Liu, Y.; Zhang, J.; Li, Y.; Huang, G. Optimal Design of Multi-Energy Complementary Power Generation System Considering Fossil Energy Scarcity Coefficient under Uncertainty. *J. Clean. Prod.* **2020**, *274*, 122732. [CrossRef]
6. Ramachandran, E.; Krishnaiah, R.; Venkatesan, E.P.; Parida, S.; Reddy Dwarshala, S.K.; Khan, S.A.; Asif, M.; Linul, E. Prediction of RCCI Combustion Fueled with CNG and Algal Biodiesel to Sustain Efficient Diesel Engines Using Machine Learning Techniques. *Case Stud. Therm. Eng.* **2023**, *51*, 103630. [CrossRef]
7. Bitire, S.O.; Jen, T.C. Performance and Emission Analysis of a CI Engine Fueled with Parsley Biodiesel–Diesel Blend. *Mater. Renew. Sustain. Energy* **2022**, *11*, 143–153. [CrossRef]
8. Sonachalam, M.; Jayaprakash, R.; Manieniyan, V.; Raghavendra Rao, P.S.; Vinodhini, G.; Sharma, M.; Kalyani, T.; Warimani, M.; Majdi, H.S.; Khan, T.M.Y.; et al. Performance Analysis of Dual-Fuel Engines Using Acetylene and Microalgae Biodiesel: The Role of Fuel Injection Timing. *Case Stud. Therm. Eng.* **2024**, *64*, 105370. [CrossRef]

9. Tiwari, C.; Dwivedi, G.; Verma, T.N. Exploring the Performance and Emission Characteristics of a Dual Fuel CI Engine Using Microalgae Biodiesel and Diesel Blend: A Machine Learning Approach Using ANN and Response Surface Methodology. *Environ. Dev. Sustain.* **2024**. [CrossRef]
10. Imdadul, H.K.; Masjuki, H.H.; Kalam, M.A.; Zulkifli, N.W.M.; Alabdulkarem, A.; Rashed, M.M.; Teoh, Y.H.; How, H.G. Higher Alcohol-Biodiesel-Diesel Blends: An Approach for Improving the Performance, Emission, and Combustion of a Light-Duty Diesel Engine. *Energy Convers. Manag.* **2016**, *111*, 174–185. [CrossRef]
11. Sanjeevannavar, M.B.; Banapurmath, N.R.; Kumar, V.D.; Sajjan, A.M.; Badruddin, I.A.; Vadlamudi, C.; Krishnappa, S.; Kamangar, S.; Baig, R.U.; Khan, T.M.Y. Machine Learning Prediction and Optimization of Performance and Emissions Characteristics of IC Engine. *Sustainability* **2023**, *15*, 13825. [CrossRef]
12. Thangaraja, J.; Zigan, L.; Rajkumar, S. A Machine Learning Framework for Evaluating the Biodiesel Properties for Accurate Modeling of Spray and Combustion Processes. *Fuel* **2023**, *334*, 126573. [CrossRef]
13. Aghbashlo, M.; Peng, W.; Tabatabaei, M.; Kalogirou, S.A.; Soltanian, S.; Hosseinzadeh-Bandbafha, H.; Mahian, O.; Lam, S.S. Machine Learning Technology in Biodiesel Research: A Review. *Prog. Energy Combust. Sci.* **2021**, *85*, 100904. [CrossRef]
14. Lage, C.S.; de Morais Hanriot, S.; Zárate, L.E. Using Artificial Neural Networks to Represent a Diesel–Biodiesel Engine. *J. Braz. Soc. Mech. Sci. Eng.* **2020**, *42*, 575. [CrossRef]
15. Awogbemi, O.; Von Kallon, D.V. Application of Machine Learning Technologies in Biodiesel Production Process—A Review. *Front. Energy Res.* **2023**, *11*, 1122638. [CrossRef]
16. Sharma, P.; Sharma, A.K.; Balakrishnan, D.; Manivannan, A.; Chia, W.Y.; Awasthi, M.K.; Show, P.L. Model-Prediction and Optimization of the Performance of a Biodiesel—Producer Gas Powered Dual-Fuel Engine. *Fuel* **2023**, *348*, 128405. [CrossRef]
17. Soudagar, M.E.M.; Shelare, S.; Marghade, D.; Belkhode, P.; Nur-E-Alam, M.; Kiong, T.S.; Ramesh, S.; Rajabi, A.; Venu, H.; Yunus Khan, T.M.; et al. Optimizing IC Engine Efficiency: A Comprehensive Review on Biodiesel, Nanofluid, and the role of Artificial Intelligence and Machine Learning. *Energy Convers. Manag.* **2024**, *307*, 118337. [CrossRef]
18. Seela, C.R.; Kalabarige, L.R.; Kattela, S.P. Machine Learning-Based Modeling of Variable Compression Ratio Engine Performance and Emissions with JME-ZnO Nanoemulsion. *Energy Sources Part A Recover. Util. Environ. Eff.* **2024**, *46*, 6038–6048. [CrossRef]
19. Shateri, A.; Yang, Z.; Xie, J. Utilizing Artificial Intelligence to Identify an Optimal Machine Learning Model for Predicting Fuel Consumption in Diesel Engines. *Energy AI* **2024**, *16*, 100360. [CrossRef]
20. Khoobbakht, G.; Najafi, G.; Karimi, M.; Akram, A. Optimization of Operating Factors and Blended Levels of Diesel, Biodiesel and Ethanol Fuels to Minimize Exhaust Emissions of Diesel Engine Using Response Surface Methodology. *Appl. Therm. Eng.* **2016**, *99*, 1006–1017. [CrossRef]
21. Arunyanart, P.; Simasatitkul, L.; Juyploy, P.; Kotluklan, P.; Chanbumrung, J.; Seeyangnok, S. The Prediction of Biodiesel Production Yield from Transesterification of Vegetable Oils with Machine Learning. *Results Eng.* **2024**, *24*, 103236. [CrossRef]
22. Yaşar, H.; Çağıl, G.; Torkul, O.; Şişci, M. Cylinder Pressure Prediction of An HCCI Engine Using Deep Learning. *Chin. J. Mech. Eng.* **2021**, *34*, 7. [CrossRef]
23. Sugumaran, V.; Thangavel, V.; Vijayaragavan, M.; Subramanian, B.; JS, F.J.; Varuvel, E.G. Efficacy of Machine Learning Algorithms in Estimating Emissions in a Dual Fuel Compression Ignition Engine Operating on Hydrogen and Diesel. *Int. J. Hydrogen Energy* **2023**, *48*, 39599–39611. [CrossRef]
24. Zandie, M.; Ng, H.K.; Gan, S.; Muhamad Said, M.F.; Cheng, X. Multi-Input Multi-Output Machine Learning Predictive Model for Engine Performance and Stability, Emissions, Combustion and Ignition Characteristics of Diesel-Biodiesel-Gasoline Blends. *Energy* **2023**, *262*, 125425. [CrossRef]
25. Genet, N.; Menelik, M.; Mekonen, W.; Gzate, Y.; Leul, A.; Demisie, F. Experimental Investigation on Diesel Engine Performance and Emission Characteristics Using Waste Cooking Oil Blended with Diesel as Biodiesel Fuel. *Discov. Energy* **2024**, *4*, 26. [CrossRef]
26. Gad, M.S.; Fawaz, H.E. Artificial Neural Network Based Forecasting of Diesel Engine Performance and Emissions Utilizing Waste Cooking Biodiesel. *Sci. Rep.* **2024**, *14*, 21980. [CrossRef]
27. Viswanathan, V.K.; Kaladgi, A.R.; Thomai, P.; Ağbulut, Ü.; Alwetaishi, M.; Said, Z.; Shaik, S.; Afzal, A. Hybrid Optimization and Modelling of CI Engine Performance and Emission Characteristics of Novel Hybrid Biodiesel Blends. *Renew. Energy* **2022**, *198*, 549–567. [CrossRef]
28. Ong, H.C.; Milano, J.; Silitonga, A.S.; Hassan, M.H.; Shamsuddin, A.H.; Wang, C.T.; Indra Mahlia, T.M.; Siswantoro, J.; Kusumo, F.; Sutrisno, J. Biodiesel Production from Calophyllum inophyllum-Ceiba Pentandra Oil Mixture: Optimization and Characterization. *J. Clean. Prod.* **2019**, *219*, 183–198. [CrossRef]
29. Şahin, S. Comparison of Machine Learning Algorithms for Predicting Diesel/Biodiesel/Iso-Pentanol Blend Engine Performance and Emissions. *Heliyon* **2023**, *9*, e21365. [CrossRef] [PubMed]
30. Ağbulut, Ü.; Gürel, A.E.; Sarıdemir, S. Experimental Investigation and Prediction of Performance and Emission Responses of a CI Engine Fuelled with Different Metal-Oxide Based Nanoparticles–Diesel Blends Using Different Machine Learning Algorithms. *Energy* **2021**, *215*, 119076. [CrossRef]

31. Nagar, H.; Machavaram, R.; Kulkarni, P.; Soni, P. AI-Based Engine Performance Prediction Cum Advisory System to Maximise Fuel Efficiency and Field Performance of the Tractor for Optimum Tillage. *Syst. Sci. Control Eng.* **2024**, *12*, 2347936. [CrossRef]
32. Miller Jothi, N.K.; Nagarajan, G.; Renganarayanan, S. Experimental studies on homogeneous charge CI engine fueled with LPG using DEE as an ignition enhancer. *Renew. Energy* **2007**, *32*, 1581–1593. [CrossRef]
33. Dora, N.; Jothi, T.J.S. Emission Studies in CI Engine Using LPG and Palm Kernel Methyl Ester as Fuels and Di-Ethyl Ether as an Additive. *J. Inst. Eng. Ser. C* **2019**, *100*, 627–634. [CrossRef]