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Review

Artificial Intelligence in Automotives: ANNs' Impact on Biodiesel Engine Performance and Emissions

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Abstract: This paper explores the integration and advancements of artificial neural networks (ANNs) in modeling diesel engine performance, particularly focusing on biodiesel-fueled engines. ANNs have emerged as a vital tool in predicting and optimizing engine parameters, contributing to the enhancement of fuel efficiency and a reduction in emissions. The novelty of this review lies in its critical analysis of the existing literature on ANN applications in biodiesel engines, identifying gaps in optimization and emission control. While ANNs have shown promise in predicting engine parameters, fuel efficiency, and emission reduction, this paper highlights their limitations and areas for improvement, especially in the context of biodiesel-fueled engines. The integration of ANNs with big data and sophisticated algorithms paves the way for more accurate and reliable engine modeling, essential for advancing sustainable and eco-friendly automotive technologies. This research underscores the growing importance of ANNs in optimizing biodiesel-fueled diesel engines, aligning with global efforts towards cleaner and more sustainable energy solutions.

Keywords: biofuel; artificial neural networks; CI engine; exhaust emissions; engine performance

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1. Introduction

The diminishing reserves of crude oil and growing global concerns over environmental pollution have prompted researchers to explore clean energy technologies and environmentally friendly alternative fuels, such as biodiesel, alcohols, vegetable oils, and hydrogen [1–3]. In the evolving landscape of energy production and utilization, diesel engines have long been recognized for their efficiency and reliability. These engines have powered a diverse range of machinery, from small vehicles to massive ships, playing an essential role in both local and global economies. However, the environmental impacts of diesel engines, particularly their contribution to greenhouse gas emissions, have raised concerns, driving a shift towards sustainable alternatives [4].

Biodiesel and higher alcohols have garnered particular attention due to their potential as sustainable alternatives for diesel engines. Biodiesel, composed of mono-alkyl esters derived from long-chain fatty acids, is typically produced through the transesterification of animal fats or vegetable oils. Its popularity has been increasing over the years, largely due to its numerous benefits over conventional diesel, including renewability, biodegradability, non-toxicity, and a higher flash point, making it a safer and more eco-friendly fuel option [5–7]. Biodiesel has emerged as a promising alternative to traditional diesel fuel. Biodiesel is compatible with existing diesel engines and has a significantly lower environmental impact than traditional diesel. It reduces carbon emissions, aligns with global sustainable energy efforts, and mitigates the reliance on fossil fuels. Studies have shown that biodiesel blends can effectively run in unmodified diesel engines, providing a feasible solution for reducing the ecological footprint of these engines [8–10].

Alongside the advancement of renewable energy sources like biodiesel, the field of engineering has seen significant developments with the integration of artificial neural networks (ANNs). ANNs, a branch of artificial intelligence, mimic the human brain's structure and functions, opening up new possibilities in problem solving and automation. In the context of engineering, ANNs have demonstrated remarkable potential in optimizing processes, enabling predictive maintenance, and increasing operational efficiency. This integration signifies a paradigm shift, leveraging AI to enhance engineering applications [11,12].

The intersection of biodiesel utilization in diesel engines and the application of ANNs in enhancing their performance and sustainability presents a fascinating area of study. This review aims to explore the recent developments at this intersection, highlighting the importance of combining renewable energy solutions with advanced AI technologies. The focus is on how these technologies can collectively contribute to mitigating environmental impacts and advancing sustainable practices in energy production and consumption. The utilization of biodiesel in diesel engines, coupled with the optimization capabilities of ANNs, holds significant promise for the future of energy sustainability [13,14].

This review aims to offer a novel contribution by precisely outlining the goals of implementing artificial neural networks (ANNs) in the context of biodiesel-fueled engine performance and emission control. The specific objectives of this review are:

1. To assess the potential applicability of ANNs in accurately predicting the performance and emission characteristics of diesel engines fueled with biodiesel.
2. To systematically review the application of ANNs in predicting the critical parameters of diesel engines.
3. To explore the potential and future prospects of using ANNs for predicting the performance and emissions of diesel engines fueled by biodiesel as an emerging green biofuel.

By systematically addressing these objectives, this review provides a deeper understanding of how ANNs can enhance engine performance and emission control in biodiesel engines.

2. Fundamentals of Diesel Engines and Biodiesel

Diesel engines operate distinctively compared to gasoline engines, primarily through the principle of compression ignition. Air in a diesel engine is compressed to high pressure and temperature, followed by fuel injection into the combustion chamber. The intense heat from the compressed air spontaneously ignites the fuel, eliminating the need for a spark plug. This process results in higher efficiency and greater torque than gasoline engines. However, conventional diesel fuels pose environmental concerns. They contribute significantly to air pollution by emitting particulate matter, nitrogen oxides, and other pollutants, impacting health and the environment. Moreover, their petroleum-based nature contributes to global greenhouse gas emissions, intensifying climate change issues [15,16]. Biodiesel emerges as a promising alternative in this scenario. Produced from renewable sources, such as vegetable oils, animal fats, or recycled cooking grease, biodiesel undergoes transesterification to convert fats and oils into fatty acid methyl esters, its main constituents. This biofuel is biodegradable and nontoxic, and its usage significantly reduces the emissions of particulates and greenhouse gases compared to traditional diesel [17,18].

Using biodiesel in diesel engines has several benefits. It reduces the ecological footprint by lowering greenhouse gas emissions and fossil fuel dependence. Biodiesel's excellent lubricity also benefits engine operation. However, there are challenges, such as issues with performance in cold weather, material compatibility problems, and inconsistent fuel quality standards [19,20]. Biodiesel, derived from renewable sources, such as spirulina microalgae and waste cooking oil, has shown significant advantages in reducing harmful emissions. One of the most critical emissions associated with biodiesel combustion is nitrogen oxides (NO_X). Research by Zheng and Cho (2023) indicates that, while biodiesel can reduce CO and HC emissions, it often leads to an increase in NO_X emissions due to its higher oxygen content, which promotes more complete combustion [21]. This trend is corroborated by Khujamberdiev (2023, 2024), who found that increasing biodiesel content in diesel blends resulted in higher NO_X emissions, particularly in blends derived from waste swine oil [22,23]. For instance, studies by Rajak et al. (2021, 2022) demonstrated that biodiesel blends can lead to substantial reductions in carbon monoxide (CO), hydrocarbon (HC), and particulate matter (PM) emissions when used in compression ignition (CI) engines. Additionally, the oxygenated nature of biodiesel promotes more complete combustion, resulting in cleaner exhaust gases. However, the use of biodiesel also presents certain challenges, particularly in terms of engine performance. While biodiesel blends effectively lower emissions, they have been shown to slightly reduce brake thermal efficiency (BTE) and mechanical efficiency, especially at higher blend ratios. Furthermore, the higher oxygen content of biodiesel can lead to increased nitrogen oxide (NO_X) emissions due to elevated combustion temperatures. These findings underscore both the advantages and challenges of biodiesel as a sustainable fuel for diesel engines, necessitating further optimization to balance emission reductions with engine performance [24,25]. The role of ANNs in this context is to optimize engine parameters to mitigate NO_X emissions. For instance, Jaliliantabar et al. (2018) utilized an ANN to model the performance and emissions of a compression ignition engine, achieving a reduction in NO_X emissions by fine-tuning the operational parameters [26].

3. Mechanism and Classification of ANN

Artificial neural networks (ANNs) are a fundamental component of artificial intelligence, drawing inspiration from the structure and function of the human brain. ANNs consist of interconnected units or nodes, mimicking biological neurons, and are adept at processing complex patterns and solving multifaceted problems. The working principles of ANNs are rooted in their structure, comprising input, hidden, and output layers, with each neuron in one layer connected to neurons in the subsequent layer [27]. The input layer receives data, which is then processed by one or more hidden layers. These hidden layers perform complex computations using the input data and transfer the processed information to the output layer, generating the desired result. The strength of the connections between neurons, known as weights, plays a crucial role in the network's learning process. Through a method known as backpropagation, ANNs adjust these weights iteratively based on the difference between the actual output and the desired output, improving the accuracy of predictions or classifications over time [28,29].

It is essential to recognize that the artificial neural network (ANN) falls under supervised learning, as it is trained based on input parameters and corresponding output data. The primary role of the learning algorithm (LA) in this context is to fine-tune the network parameters, including weights and biases, ensuring predictions are made with reasonable accuracy or within acceptable error margins. This is why the error signal, often represented by the mean squared error, is commonly utilized as the cost function. Once the training phase is complete, the testing and validation stages become crucial, offering comprehensive insights into the efficacy of the technologically advanced ANN prediction models. The effectiveness of the training, validation, and testing processes is typically gauged using the correlation coefficient (R) and the coefficient of determination (R^2). Validation involves feeding a new set of input data to the network to assess its predictive capabilities [30].

Moreover, to evaluate the accuracy of the predicted responses, additional statistical analyses, such as the root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute percentage (MAP), mean squared relative error (MSRE), mean error percentage (MEP), mean relative error (MRE), among others, are frequently conducted. The various stages of ANN implementation, encompassing these elements, are depicted in Figure 1, providing a visual roadmap of the process from training to validation [31].

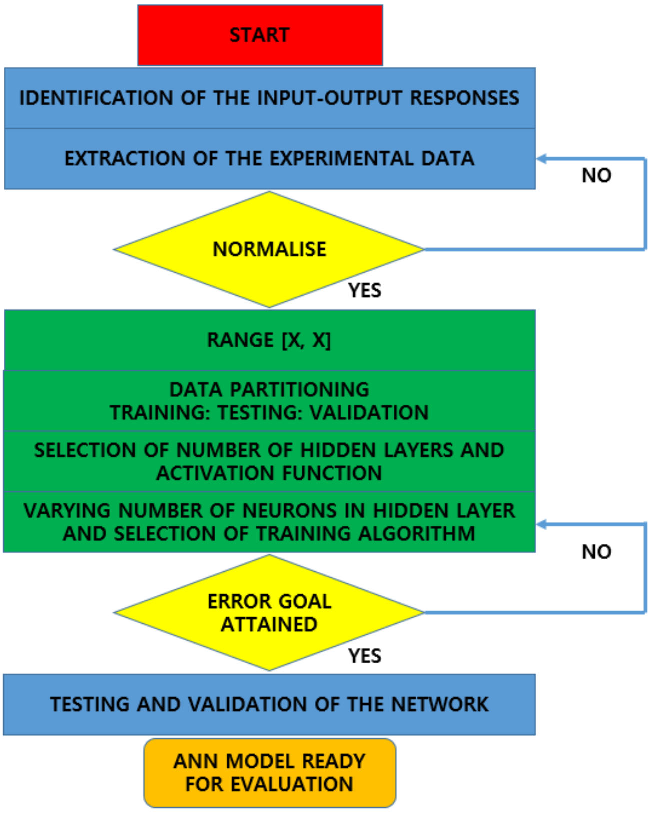

Figure 1. Process diagram of ANN model development and deployment [31].

ANNs are utilized in diverse applications, showcasing their versatility and adaptability. For instance, they are used in environmental risk assessments, where they can predict pollution levels and assess health risks based on various environmental factors [32]. In the field of robotics, ANNs are employed to solve complex inverse kinematics problems, optimizing robotic movements for efficiency and precision [33]. Additionally, in the renewable energy sector, ANNs are applied to detect faults in photovoltaic systems, enhancing the reliability and safety of solar power installations [34].

The scope of ANN applications extends further into areas like biomedical engineering, where they assist in creating advanced diagnostic tools, and even in geotechnical engineering, where they contribute to the analysis and prediction of soil behavior and material properties. This wide range of applications demonstrates the potential of ANNs as a transformative tool in various scientific and technological fields, enabling more efficient and intelligent solutions to complex problems [29,32].

Artificial neural networks (ANNs) have become integral in advancing the capabilities of various engineering fields, owing to their resemblance to human brain functioning and adaptability in learning from data. Abiodun et al. [35] provide a comprehensive survey of ANN applications, highlighting their wide-ranging use across diverse domains. The basic principle of ANNs involves interconnected neurons processing input data in a layered structure, a concept extensively covered by Shanmuganathan [36]. This layered approach, combined with learning algorithms, like backpropagation, enables ANNs to make sophisticated predictions and decisions.

4. ANN in Diesel Engine Performance with Biodiesel

Various types of ANN architectures have been utilized in this context, with the most common being the backpropagation neural network (BPNN) and radial basis function neural networks (RBFNNs). For instance, in the study by Panda et al., a BPNN was used to model the performance and emissions of a diesel engine fueled with waste plastic pyrolytic oil, demonstrating the model's capability to predict engine behavior based on varying fuel blends. The BPNN was trained using experimental data collected from engine tests, allowing it to learn the complex relationships between biofuel properties and engine performance metrics. The effects of specific biofuel properties, such as viscosity, density, and cetane number, on engine performance have been a focal point in many studies [37]. For example, Tosun et al. utilized an ANN to predict emissions and performance metrics of diesel engines fueled with biodiesel, emphasizing the influence of cetane number and other fuel properties on engine output [38]. The ANN model was able to correlate these properties with performance outcomes, providing insights into how variations in biofuel composition can affect engine efficiency and emissions. This predictive capability is crucial for optimizing biofuel formulations to enhance engine performance, while minimizing harmful emissions. Moreover, the application of RBFNNs has shown promise in predicting engine performance characteristics when using biofuels. In the work by Pai and Rao, RBFNNs were employed to predict the performance and emission characteristics of a diesel engine fueled with waste cooking oil (WCO) [39]. The RBFNN was trained with input parameters, such as load percentage, compression ratio, and blend percentage, while output parameters included brake thermal efficiency and exhaust emissions. The results indicated that RBFNNs could effectively capture the nonlinear relationships inherent in the combustion process, leading to accurate predictions of engine performance. The integration of ANN models with experimental data has been pivotal in enhancing the accuracy of predictions related to biofuel properties. For instance, Karagöz's study demonstrated that an ANN could predict engine performance and emissions for a single-cylinder diesel engine fueled with various blends of pyrolytic oil and butanol [40]. By systematically varying engine loads and fuel compositions during experiments, the ANN was trained to recognize patterns in the data, resulting in reliable predictions of performance metrics, such as brake specific fuel consumption and emissions. In addition to BPNN and RBFNN, other advanced ANN techniques, such as adaptive neuro-fuzzy inference systems (ANFIS), have been explored for predicting biofuel effects. These hybrid models combine the learning capabilities of ANNs with fuzzy logic, allowing for better handling of uncertainties and imprecision in biofuel properties. The study by Menon and Krishnasamy illustrated the use of ANFIS to optimize biodiesel-fueled engine characteristics, showcasing its effectiveness in capturing the complexities of biofuel behavior in engines [41]. This approach provides a more nuanced understanding of how different biofuel compositions can influence engine performance. The predictive capabilities of ANNs extend beyond performance metrics to include emissions analysis. For example, the research conducted by Çirak and Demirtas focused on predicting engine torque and emissions from biodiesel using an ANN model [42]. By incorporating various input parameters, such as fuel composition and engine operating conditions, the ANN was able to provide accurate predictions of emissions, highlighting the importance of biofuel properties in determining environmental impacts. Furthermore, the ability of ANNs to model the interactions between multiple biofuel properties is a significant advantage. In a study by Garg et al., ANNs were utilized to analyze the performance and emissions of internal combustion engines across a range of fuel compositions [43]. The model's ability to integrate multiple input variables allowed for a comprehensive assessment of how different biofuel properties interact to influence engine behavior, providing valuable insights for biofuel optimization. Despite the successes of ANN models, challenges remain in ensuring their generalizability across different engine types and operating conditions. As highlighted by Wang et al., the performance of ANN models can vary significantly based on the specific characteristics of the engine and the biofuels used [44]. This necessitates the continuous refinement of ANN models through extensive experimental validation to ensure their applicability in diverse scenarios.

4.1. ANNs in Emission Analysis of Biodiesel-Fueled Diesel Engines

One of the most critical challenges in biodiesel combustion is the increase in NO_X emissions, which result from biodiesel's higher oxygen content and the subsequent rise in combustion temperatures. ANN models have been developed to specifically address this issue by incorporating combustion-related parameters. S.V. K and Masimalai (2020) explored the performance and emissions of a Mahua oil–hydrogen dual fuel engine using ANN models. The model inputs were engine load, intake temperature, and injection pressure, while outputs included brake thermal efficiency (BTE), exhaust gas temperature (EGT), and emissions (HC, CO, NO_X, and smoke). A logsig-tansig ANN architecture was employed with a 70:15:15 partitioning ratio. The results showed strong model performance, with R = 0.99818 for BTE and 0.99936 for CO. The ANN model closely aligned with experimental data, especially in predicting emissions, making it a valuable tool for optimizing hydrogen-based dual-fuel engines [45]. Similarly, Javed et al. (2015) developed an ANN model to predict the performance and emissions of a hydrogen dual-fueled diesel engine using Jatropha methyl ester (JME) biodiesel blends. The ANN model used a logsig-logsig transfer function with data normalized between [0.1, 0.9], focusing on engine load, blending ratio, and hydrogen flow rate. The model produced an R value of 0.99745 for brake specific energy consumption (BSEC) and 0.99847 for CO emissions. This study confirmed the effectiveness of logarithmic and hyperbolic tangent transfer functions, as the model closely matched the experimental results for both performance and emission characteristics [46].

In another study, Channapattana et al. (2017) focused on optimizing the engine parameters of a DI-CI engine running on second-generation biofuels, using ANN models for prediction. Input variables included engine load, compression ratio, and blend ratio, with outputs covering BTE, BSEC, EGT, CO, and other emissions. The model, based on the trainlm function and a 70:15:15 partition ratio, achieved a very high R value of 0.9999, making it highly accurate in predicting engine performance and emissions. The results indicated that combining ANN models with optimization techniques, such as genetic algorithms, yields better accuracy and lower errors in modeling engine behavior with biofuels [47]. Tosun et al. (2016) compared linear regression models with ANN models for diesel engines running on biodiesel–alcohol mixtures. The ANN model, utilizing a logsig-trainlm architecture and an 80:20 partition ratio, modeled engine speed and fuel properties as input parameters, with torque and NO_X emissions as outputs. The ANN model achieved an R^2 of 0.726 for torque and 0.898 for NO_X, showing a significant improvement in predictive capability compared to linear regression models. This demonstrates that ANNs offer superior accuracy in analyzing engine performance using biodiesel–alcohol mixtures [48]. To further improve model accuracy, Gul et al. (2019) combined grey Taguchi and ANN-based optimization techniques to enhance engine performance and emissions in diesel engines fueled with biodiesel. The input variables included engine load, engine speed, and blending ratio, while outputs were the heat release rate (HRR), brake power, and emissions. The logsig-tansig-purelin model, using a 70:15:15 partition ratio, provided an R value of 0.99333. By integrating ANNs with grey Taguchi methods, the study improved model accuracy and reduced experimental time and cost, demonstrating its potential for optimizing biodiesel-fueled engine performance [49]. Aydın et al. (2020) also applied advanced modeling techniques by combining ANNs and response surface methodology (RSM) to predict the performance and emissions of a compression ignition engine fueled with biodiesel–diesel blends. The input variables were engine load and blending ratio, and the outputs included BTE, EGT, HC, NO_X, and smoke. The model used a trainlm-logsig function and a 75:25 training/testing ratio. The ANN model demonstrated a mean relative error (MRE) of 0.0592 for BTE and high R^2 values (0.97–0.99) for emissions, making it an effective tool for predicting performance and emissions in complex engine systems [50]. Shivakumar et al. (2010) examined the performance and emissions of a four-stroke CI engine using honge methyl ester (HME) biodiesel blends. The input parameters included engine load and blending ratio, with outputs of BTE, EGT, CO, NO_X, HC, and smoke. The ANN model, built with a trainlm-tansig function and normalized between [−1, 1], achieved an R value of 0.996 for BTE and 0.984 for CO emissions. The use of genetic algorithms in tandem with ANN models helped optimize engine performance, particularly in reducing emissions and improving thermal efficiency when using biodiesel blends [51]. Oğuz et al. (2010) took a different approach by developing an ANN model to predict diesel engine performance using various biofuel blends. The model utilized a tansig transfer function to predict power, torque, and BSFC. With high R^2 values of 0.99989 for torque and 0.99999 for BTE, the model demonstrated excellent reliability, calculated at 99.94%. This ANN model proved highly effective in simulating engine performance with biofuel blends, highlighting its potential for optimizing engine parameters in real time [52]. Sharon et al. (2012) applied a SIMULINK-based ANN model to predict the performance of diesel engines using biodiesel blends. Input variables included engine load and blending ratio, while outputs were BTE, BSFC, CO, NO_X, and HC. The tansig-trainlm model achieved R values of 0.999 for BTE and 0.99998 for BSFC. The study showed that the SIMULINK environment allowed for the accurate and user-friendly modeling of engine behavior, making it an efficient tool for analyzing higher biodiesel blends in compression ignition engines [53]. The studies reviewed demonstrate that ANN models, often combined with optimization techniques, have proven to be highly effective tools in predicting engine performance and emissions across a range of biodiesel and alternative fuel applications. Table 1 summarizes key studies on ANNs in emission analysis of biodiesel-fueled diesel engines.

Table 1. Key studies on ANN in emission analysis of biodiesel-fueled diesel engines.

Author(s)	Focus of Study	Key Insights	R Values or Accuracy	Reference
S.V. K and Masimalai (2020)	Mahua oil–hydrogen dual-fuel engine emissions and performance using ANN.	ANN predicted BTE, EGT, HC, CO, NO_X, and smoke with strong alignment to experimental data.	R = 0.99818 (BTE), 0.99936 (CO)	[45]
Javed et al. (2015)	Hydrogen dual-fueled diesel engines using Jatropha methyl ester (JME) blends.	Effective use of logsig-logsig transfer function for performance and emission predictions.	R = 0.99745 (BSEC), 0.99847 (CO)	[46]
Channapattana et al. (2017)	DI-CI engine with second-generation biofuels.	ANN with trainlm function yielded high accuracy in predicting emissions and performance.	R = 0.9999	[47]
Tosun et al. (2016)	Comparison of linear regression and ANN for biodiesel–alcohol engine emissions.	ANN significantly outperformed linear regression, modeling torque, and NO_X emissions with superior accuracy.	R^2 = 0.726 (torque), 0.898 (NO_X)	[48]
Gul et al. (2019)	Grey Taguchi and ANN for engine optimization using biodiesel.	Integration of ANN with Grey Taguchi improved accuracy and reduced experimental costs.	R = 0.99333	[49]
Aydın et al. (2020)	ANN-RSM model for CI engines fueled with biodiesel–diesel blends.	Predicted BTE, EGT, HC, NO_X, and smoke with high R^2 values and low mean relative error.	R^2 = 0.97–0.99 (emissions), MRE = 0.0592 (BTE)	[50]

Table 1. *Cont.*

Author(s)	Focus of Study	Key Insights	R Values or Accuracy	Reference
Shivakumar et al. (2010)	Performance and emissions using honge methyl ester (HME) biodiesel blends.	ANN with genetic algorithms optimized emissions and thermal efficiency.	R = 0.996 (BTE), 0.984 (CO)	[51]
Oğuz et al. (2010)	ANN for predicting diesel engine performance with biofuel blends.	Achieved excellent predictive reliability for power, torque, and BSFC.	R^2 = 0.99989 (torque), 0.99999 (BTE)	[52]
Sharon et al. (2012)	SIMULINK-based ANN for diesel engines with biodiesel blends.	Highly accurate predictions of BTE and BSFC in user-friendly modeling environments.	R = 0.999 (BTE), 0.99998 (BSFC)	[53]

4.2. Application of ANNs in Predicting and Analyzing Emissions from Biodiesel-Fueled Engines

A key study by Prabhakar et al. [54] investigated the performance and emission characteristics of engines fueled with biodiesel blends derived from non-edible vegetable oils, such as nerium, jatropha, pongamia, mahua, and neem. Their findings indicated that a diesel engine could successfully run on a blend of 20% biodiesel and 80% diesel fuel without compromising engine performance. Notably, methyl esters from nerium oil exhibited better performance and emission characteristics, followed by esters from other oils, thereby highlighting the potential of ANNs in optimizing biodiesel blends for improved emissions. Samsukumar et al. [55] conducted performance and emission analysis on a compression ignition (C.I.) engine using palm oil biodiesel blends at different fuel injection pressures. Their research focused on optimizing engine parameters to reduce emissions, specifically carbon monoxide (CO) and nitrogen oxides (NO_X), using biodiesel blends. The study utilized advanced tools, including a computerized variable compression ratio multifuel direct injection water-cooled engine and a six-gas smoke analyzer, to analyze the emissions under various operating conditions. Figure 2 illustrates the correlation between various input parameters, output parameters, and hidden layers in predicting engine performance and emissions when using biodiesel. The input parameters include fuel properties, such as types of biodiesel and their blends, and engine variables like engine speed, loads, compression ratios, injection pressure, and timing. On the other hand, the output parameters represent engine performance metrics, including power, exhaust gas temperature, specific fuel consumption, torque, and brake thermal efficiency, along with emission characteristics like CO, HC, CO_2, NO_X, and smoke. Predicting engine performance and emissions using ANN models involves numerous input variables and output parameters, but excessive inputs or outputs can hinder model training and accuracy. The careful selection of inputs, hidden layers, and outputs is crucial. Jaliliantabar et al. [26] found a 3–8–9 architecture optimal for predicting effective power after 150 epochs, using inputs like engine speed, load, and biodiesel blend ratio. The model achieved R^2 values close to 1 for performance predictions, ranging from 0.93 (EGT) to 0.98 (torque). Emission predictions showed slightly lower accuracy, with a maximum R^2 of 0.94 for CO emissions.

El-Shafay et al. [56] utilized ANNs to predict performance and emissions in diesel engines fueled with palm biodiesel. Their study demonstrates how ANNs can handle the variability in biodiesel blends and their impact on engine emissions. Similarly, Uslu et al. [57] predicted the emissions and performance of a diesel engine using diethyl ether and biodiesel mixtures, illustrating the versatility of ANNs in emission analysis. Franco et al. [58] explored the impact of transition teams and social interactions on sustainable energy innovation. Their study, focusing on NO_X and particulate matter reduction, highlights the role of ANNs in advancing technologies for cleaner energy. This approach is pivotal in transitioning to sustainable practices and reducing environmental pollutants in various sectors, including automotive engineering. Okubo et al. [59] conducted research on improving NO_X reduction efficiency in diesel emissions using nonthermal plasma combined with exhaust gas recirculation as an after-treatment. Their study suggests that ANNs can be effectively utilized in designing and optimizing these systems for enhanced NO_X reduction in diesel engines. Such advancements are critical in meeting stringent emission regulations and promoting cleaner combustion processes. Veratti et al. [60] assessed the impact of NO_X and NH3 emission reduction on particulate matter across the Po Valley. Their research indicates that ANN models are instrumental in analyzing the nonlinear responses of $PM_{2.5}$ concentrations to precursor changes. By employing ANNs in air quality modeling systems, significant insights can be gained into the most efficient emission reduction strategies, contributing to improved air quality and public health. Urrutia-Mosquera at al. [61] examined the impact of confinement on pollution and particulate matter reduction. Their reflections on public transport policies underscore the potential of ANNs in predicting and strategizing effective approaches to reduce emissions in urban environments, thereby contributing to cleaner and healthier cities. In addition, Sayyed et al. [62] focused specifically on modeling biodiesel-emitted nitrogen oxides using ANNs. Their research highlights the importance of ANNs in understanding and reducing NO_X emissions in biodiesel engines. Ertuğrul at al. [63] further demonstrated ANNs' role in predicting the performance and emission parameters of a biodiesel-fueled diesel generator, emphasizing the accuracy of ANNs in emission analysis.

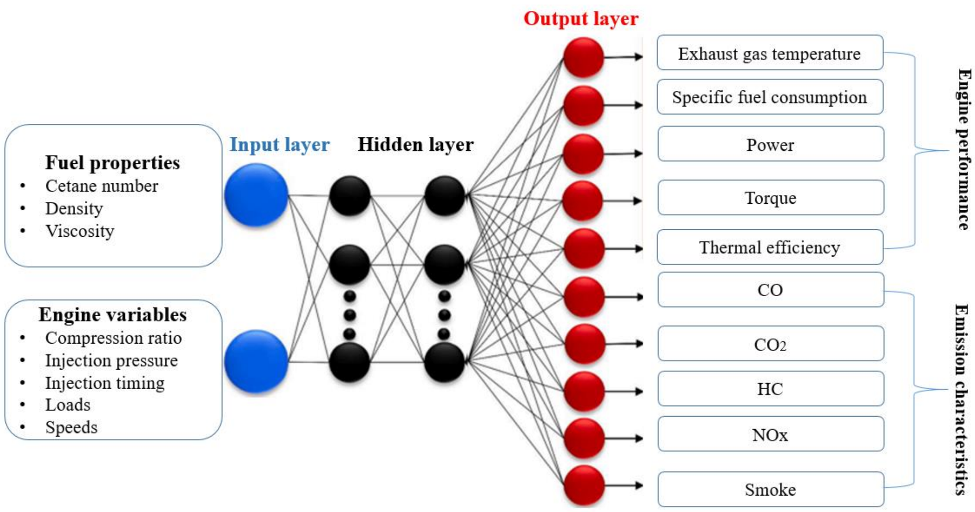

Figure 2. ANN architecture for predicting engine behavior [56].

These studies collectively emphasize the significance of ANNs in understanding and mitigating emissions from biodiesel-fueled engines. The sophisticated predictive and analytical capabilities of ANNs make it an indispensable tool in advancing emission control technologies and supporting the transition towards more sustainable and environmentally friendly energy solutions. A notable study by Kannan at al. [64] conducted an emission analysis of Azolla methyl ester with BaO nanoadditives for internal combustion engines. This research focused on decreasing emissions in diesel engines fueled with biodiesel and algae biodiesel blends, with the addition of BaO nanoparticles. The results showed that the addition of nanoparticles reduced emissions, such as carbon monoxide (CO), hydrocarbons (HC), and oxygen (O_2) from biodiesel, emphasizing the role of ANNs in emission reduction strategies. In another significant study, Samsukumar et al. [55] performed performance and emission analyses on a compression ignition (C.I.) engine using palm oil biodiesel blends at different fuel injection pressures. Their research aimed to examine biodiesel properties, engine performance, and emissions, with a focus on reducing CO and NO_X emissions. Utilizing ANNs, the study provided insights into the emissions pattern and performance of biodiesel blends, underscoring the potential of ANNs in optimizing biodiesel fuel for cleaner engine performance. Prabhakar at al. [54] explored biodiesels as an alternative renewable energy source for the next century, examining the performance and emission characteristics of engines fueled with various biodiesel blends. Their findings indicated that certain biodiesel blends could run in diesel engines without affecting performance, with notable improvements in emission characteristics. This study highlighted the potential of ANNs in identifying suitable biodiesel blends for emission reduction. Table 2 highlights studies on ANN applications in optimizing emissions and performance of biodiesel-fueled engines.

Table 2. Key studies on the application of ANNs in predicting and analyzing emissions from biodiesel-fueled engines.

Author(s)	Focus of Study	Key Insights
Prabhakar et al. [54]	Investigated engines using biodiesel blends from nonedible oils (e.g., nerium, jatropha, pongamia).	Identified a 20% biodiesel blend that maintained performance; highlighted ANNs' role in optimizing blends.
Samsukumar et al. [55]	Analyzed C.I. engine emissions using palm oil biodiesel blends at different injection pressures.	Optimized parameters to reduce CO and NO_X using ANN; utilized advanced tools for precise emission analysis.
Jaliliantabar et al. [26]	Examined ANN architectures for predicting engine performance with biodiesel blends.	Found a 3–8–9 architecture optimal for predictions; achieved R^2 values of 0.93–0.98 for various metrics.
El-Shafay et al. [56]	Predicted emissions and performance of diesel engines with palm biodiesel using ANNs.	Demonstrated ANNs' capability to handle biodiesel blend variability and predict emissions effectively.
Uslu et al. [57]	Predicted diesel engine emissions using diethyl ether and biodiesel mixtures.	Highlighted the versatility of ANNs in emission analysis.
Franco et al. [58]	Investigated ANNs' role in NO_X and particulate matter reduction for sustainable energy innovation.	Demonstrated ANNs' utility in advancing cleaner energy technologies and reducing pollutants.
Okubo et al. [59]	Researched NO_X reduction using nonthermal plasma and EGR optimized with ANNs.	Showed ANNs' effectiveness in improving after-treatment systems for NO_X reduction.
Veratti et al. [60]	Studied NO_X and NH_3 emission reduction impacts on particulate matter in the Po Valley.	Emphasized ANNs' utility in modeling nonlinear responses of $PM_{2.5}$ to emission changes.
Urrutia-Mosquera et al. [61]	Explored ANNs' application in urban emission reduction during confinement.	Highlighted ANNs' predictive power in strategizing urban emission policies for cleaner cities.
Sayyed et al. [62]	Modeled biodiesel-emitted NO_X emissions using ANN.	Showed ANNs' role in understanding and reducing NO_X in biodiesel engines.
Ertuğrul et al. [63]	Predicted performance and emissions of biodiesel-fueled diesel generators with ANNs.	Demonstrated ANNs' accuracy in emission analysis.
Kannan et al. [64]	Analyzed emissions in engines using biodiesel–algae blends with BaO nanoparticles.	Found significant reductions in CO, HC, and O_2 emissions, emphasizing ANNs' role in emission strategies

5. Challenges and Limitations in Using ANNs for Biodiesel-Fueled Engines

5.1. Discussion on the Limitations of Current ANN Models in Accurately Predicting Engine Performance and Emissions

A critical aspect to consider is the quality and diversity of the training data. ANNs' performance heavily relies on the data they are trained on. In the context of diesel engines, these data include a wide range of operating conditions, fuel types, and engine configurations. If the training data are not comprehensive or lack variability, the ANN models might not accurately predict engine performance under untested conditions, leading to less reliable outcomes [65]. Moreover, the complexity of diesel engine systems, especially when using biodiesel, introduces challenges in ANN modeling. Biodiesel's varying properties based on feedstock and production processes add another layer of complexity. This variability can affect engine performance in ways that might not be fully captured by existing ANN models, leading to discrepancies between predicted and actual engine behavior [66].

As illustrated in Figure 2, a multitude of input data, encompassing engine variables and fuel properties, along with numerous output parameters, require prediction. However, overloading the input layer with too much data and attempting to predict a vast array of output parameters can lead to substantial challenges in the training, learning, and structuring of the ANN model. This overload can potentially result in less accurate predictions. Therefore, it is crucial to meticulously consider the selection of relevant input data, the arrangement of hidden layers, and the determination of output parameters for more precise outcomes [67]. The generalization capability of ANNs is a concern. While ANNs are efficient in modeling specific scenarios based on their training, their ability to generalize to new, unseen scenarios is often limited. This limitation is particularly crucial when it comes to emissions analysis, where regulatory standards are stringent and require precise adherence [68]. The limited solubility and viscosity differences between ethanol and diesel in biodiesel blends pose another challenge. These physical property disparities can lead to phase separation and impact the lubricity of the fuel, influencing engine performance and emissions, which ANNs might not accurately predict. The training data used to develop ANN models can also impact their predictive capabilities. If the training datasets are not sufficiently diverse or representative of the operating conditions, the ANNs may fail to generalize well to new scenarios. Kolakoti's research indicated that, while ANN models could achieve high accuracy under specific conditions, their performance may degrade when applied to different biodiesel types or engine configurations [69]. This limitation emphasizes the need for extensive and varied datasets to enhance the robustness of ANN predictions.

Furthermore, developing ANN models for biodiesel engines requires expertise in both engine technology and computational modeling. This interdisciplinary requirement can be a barrier in terms of resources and knowledge, impacting the development and refinement of ANN models. One of the primary limitations is the accuracy of ANNs in predicting engine performance and emissions. Bhatt at al. [70] delve into the state-of-the-art application of ANNs in internal combustion engines, noting that the complex interactions in engine processes can be challenging for ANN models to accurately predict. This limitation is partly due to the variability in biodiesel compositions and the complex nature of combustion processes.

5.2. Cost Analysis of Biodiesel Usage and the Integration of ANNs in Engine Optimization

ANN models facilitate the prediction of engine performance metrics, such as brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), and torque, which are critical for assessing the economic viability of biodiesel as an alternative fuel. For instance, Umeuzuegbu et al. demonstrated that ANNs could effectively model engine performance based on biodiesel blends and engine speed, providing insights into the unit cost associated with biodiesel usage [71]. This predictive capability allows for a more informed decision-making process regarding the economic implications of biodiesel fuel blends. Moreover, the cost-effectiveness of biodiesel can be further analyzed through its performance characteristics. Studies have shown that the fatty acid composition of biodiesel significantly influences its fuel properties and, consequently, the engine's performance. By employing ANNs to correlate these properties, researchers can optimize biodiesel blends to achieve better performance, while minimizing costs. For example, Singh et al. highlighted the importance of understanding the relationship between biodiesel composition and engine characteristics, which can lead to more efficient fuel formulations that reduce operational costs [72]. This optimization process is crucial for commercial viability, as it directly impacts the economic feasibility of biodiesel as a substitute for conventional diesel fuels. In addition to performance metrics, the environmental benefits of biodiesel usage also play a role in cost analysis. The reduction in emissions associated with biodiesel fuels can lead to lower regulatory compliance costs and potential financial incentives for using cleaner fuels. Research has indicated that biodiesel blends can significantly reduce harmful emissions compared to traditional diesel, thus providing an economic advantage when considering the costs associated with emissions control [73]. For instance, El-Shafay et al. found that palm biodiesel blends improved engine performance, while also reducing emissions, which could translate into lower costs related to environmental compliance [56]. This dual benefit of performance enhancement and emission reduction underscores the economic potential of biodiesel. The integration of ANNs with optimization techniques, such as genetic algorithms, further enhances the cost analysis of biodiesel usage. By optimizing the biodiesel–diesel blend ratios, researchers can identify the most cost-effective combinations that yield optimal engine performance [73]. For example, the work by Najafi et al. utilized ANNs in conjunction with response surface methodology to determine the optimal blending conditions for biodiesel and diesel, demonstrating a systematic approach to cost optimization in biodiesel applications [74]. This methodology not only aids in achieving better performance but also ensures that the economic implications are thoroughly evaluated.

5.3. Challenges in Data Collection, Model Training, and Validation

Data Collection Challenges: Data collection for ANN modeling in diesel engines is multifaceted and requires an extensive and diverse dataset that captures a wide range of operating conditions, fuel types, and engine specifications. Collecting such comprehensive data is often time-consuming, expensive, and technically challenging. In the case of biodiesel, factors like the variety of feedstock sources, the production process, and the blend ratios significantly affect the fuel's properties and, consequently, the engine's performance. This variability necessitates the collection of a vast array of data to accurately train the ANN models [75]. Data collection, model training, and validation also pose significant challenges. As Aghbashlo et al. [76] observe, the quality and quantity of data available for training ANNs are crucial for their performance. Inaccurate or insufficient data can lead to models that do not accurately reflect real-world engine behavior. Furthermore, the training of ANN models to capture the nuances of biodiesel fuel characteristics and engine responses requires significant computational resources and expertise.

Model Training Difficulties: Training ANNs for diesel engine applications involves setting a large number of hyper-parameters and structuring layers and neurons in a way that can best interpret the complex relationship between inputs (like fuel properties) and outputs (such as emissions and efficiency). This process requires not only substantial computational resources but also specialized knowledge in both engine mechanics and machine learning. Additionally, ensuring that the ANN is neither underfitting nor overfitting is a delicate balance that must be achieved during training [77].

Validation Complexities: Validating ANN models is a critical step to ensure their reliability and accuracy in real-world applications. However, validating models that predict engine performance and emissions is challenging due to the dynamic and nonlinear nature of engine systems. Field tests and real-world data are essential for validation but can be difficult to obtain and may not always be representative of the broader range of operating conditions. Furthermore, for biodiesel engines, variations in fuel quality and composition across different sources add an additional layer of complexity to the validation process [78,79]. Figure 3 highlights the challenges in data collection, model training, and validation for ANN modeling in diesel engines, with a focus on biodiesel applications.

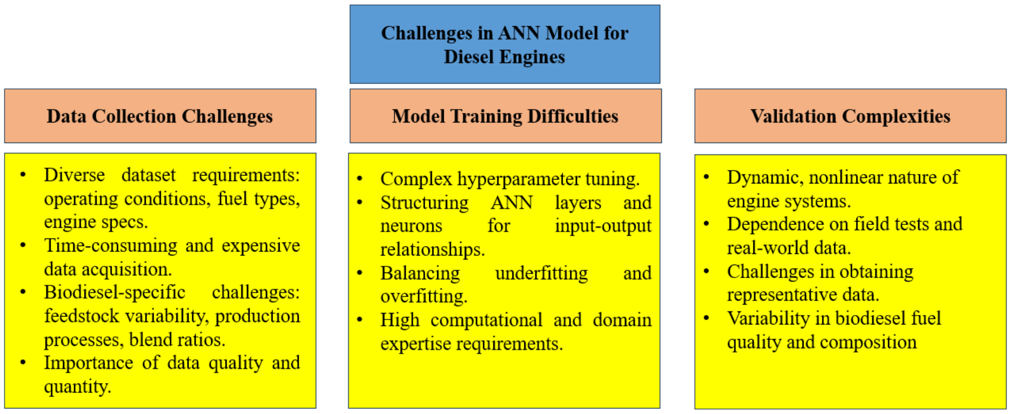

Figure 3. Challenges in ANN modeling for diesel engines.

5.4. Potential Areas of Improvement in ANN Modeling for Better Accuracy and Reliability

One area of improvement is the integration of fuzzy systems with ANNs to handle uncertainties and improve modeling capabilities. Sarma at al. [80] proposed a fuzzy neural system using a fuzzy time delay fully recurrent neural network (FTDFRNN), which tackles time-varying inputs in fuzzified form. This approach is especially useful in modeling the stochastic behavior of engine systems, allowing for better adaptation to minute variations in propagation conditions, such as those encountered in engine operations. Optimizing neural network architectures for specific applications is another area of improvement. Rozario at al. [81] conducted a performance comparison of phoneme modeling using various optimization algorithms for neural network architectures. Their study highlighted the importance of selecting the right optimization algorithm and adjusting the neural network's structure to enhance the modeling performance, which can be applied to engine modeling for more precise predictions. Manivannan [82] emphasized the significance of numerical and experimental studies in engine modeling. By combining thermodynamic and global modeling techniques, more comprehensive and accurate ANN models can be developed, especially for lean burn spark ignition engines. This approach can improve performance and emission characteristics, highlighting the need for a holistic view in ANN modeling.

Advancements in deep learning can provide significant improvements in ANN modeling. Pradeep at al. [83] demonstrated the effectiveness of deep neural networks (DNN) for Kannada phoneme recognition. The application of DNN in engine modeling, especially for handling large datasets and complex relationships, can lead to significant performance enhancements.

Lastly, forecasting engine performance and emission parameters using ANN modeling, as explored by Manimaran at al. [84], can benefit from incorporating environmental considerations. Their study on green diesel extracted from waste biomass resources underscores the potential of ANN models in promoting sustainable and eco-friendly engine technologies. Potential areas for improvement in ANN modeling include the integration of more diverse and extensive datasets and the development of more advanced algorithms that can capture the complex relationships in engine performance and emissions more accurately. Sharma's [85] comparative evaluation suggests that integrating ANNs with other computational techniques could enhance prediction accuracy.

Moreover, addressing the issue of overfitting, where models perform well on training data but poorly on unseen data, is crucial. Enhancing the generalizability of ANN models remains a key area of development. Research by Palanivelu et al. [86] into biodiesel-fueled engine analysis using ANNs highlights the need for models that can adapt to different types of biodiesel and engine configurations.

6. Future Prospects and Advancements

6.1. Emerging Trends in ANNs and Their Potential Impact on Biodiesel-Fueled Diesel Engines

A significant trend in ANN applications is observed in reactivity-controlled compression ignition engines, as elucidated by Paykani et al. [87]. Their study explores low-temperature combustion strategies, including reactivity-controlled compression ignition, which uses dual-fuel partially premixed combustion. This approach, enhanced by ANN modeling, offers greater control over combustion phasing and duration, contributing to improved fuel flexibility and combustion efficiency. Such advances are essential in reducing NO_X and particulate matter emissions, thereby promoting cleaner and more efficient diesel engine operations. Ennetta et al. [88] discussed current technologies and future trends in biodiesel production. This comprehensive review underscores the importance of advanced ANN applications in optimizing biodiesel production processes, directly impacting diesel engine performance and emissions. By enhancing biodiesel quality and efficiency, ANNs contribute to more sustainable and eco-friendly diesel engine operations. Kumar at al. [89] analyzed the performance and emission of antioxidant-treated waste cooking oil biodiesel using ANNs. This study demonstrates the potential of ANN models in enhancing biodiesel properties for improved engine efficiency and reduced emissions, reinforcing the relevance of emerging ANN trends in biodiesel research.

These emerging trends in ANN applications reflect the significant potential of these models in revolutionizing biodiesel-fueled diesel engine technology. From optimizing combustion processes to improving biodiesel production and enhancing fuel properties, ANNs are instrumental in advancing sustainable and efficient diesel engine solutions.

6.2. The Role of Big Data and Advanced Algorithms in Enhancing ANN Applications

The integration of big data and advanced algorithms with artificial neural networks (ANNs) is revolutionizing their applications, particularly in modeling biodiesel-fueled diesel engine performance. These advancements not only enhance the predictive capabilities of ANNs but also address the challenges posed by the vast and complex datasets involved in engine performance modeling [90]. Diamantoulakis at al. [91] emphasizes the need for advanced data analytics and big data management in handling the immense size of data generated by smart systems. In the context of diesel engines, this approach is crucial for dealing with the extensive data generated by various sensors and performance tests. The use of such data analytics can significantly improve the prediction accuracy of ANNs in engine modeling.

Efficient big data clustering, explored by Ianni et al. [92], presents another avenue for enhancing ANN applications. Their work on the CLUBS+ algorithm demonstrates how complex data mining algorithms can be adapted for scalable deployment on massively parallel distributed systems. This methodology is particularly relevant for ANNs in diesel engine modeling, as it allows for the effective clustering and analysis of large-scale engine performance data, leading to more accurate and reliable predictions. The role of unsupervised clustering algorithms tailored for big data applications, such as CLUBS-P, also shows promise in enhancing ANN models. This approach, as described by Ianni et al. [93], focuses on refining clustering algorithms to handle the complexity and scale of big data, which is vital for improving the performance and reliability of ANNs in engine emission analysis. The application of algorithms for big data in advanced communication systems and cloud computing, as discussed by Stergiou at al. [94], has implications for ANN applications in engine modeling. This research highlights the potential of combining big data functionalities with cloud computing to enhance the security and efficiency of data analysis, which is instrumental in optimizing ANN models for engine performance predictions.

Emerging trends in ANNs are leaning towards more complex and efficient algorithms that can handle big data effectively. Bhatt at al. [70] highlight the potential of ANNs in dealing with the intricacies of internal combustion engines, suggesting that advancements in ANNs will lead to more precise modeling and optimization. The integration of ANNs with big data analytics opens new avenues for understanding engine behavior under diverse operational conditions, leading to more refined control strategies. The role of big data in enhancing ANN applications cannot be overstated. As the volume of data from engine tests and simulations grows, the ability of ANNs to process and learn from this data will be pivotal in developing more accurate predictive models. This will lead to enhanced efficiency and emission performance of biodiesel engines [94].

Future research directions are likely to focus on hybrid models that combine ANNs with other machine learning techniques, such as genetic algorithms and deep learning. These hybrid models, as Sharma [85] suggests, can potentially overcome the limitations of current ANN models, offering more robust predictions and optimizations.

Breakthroughs in this field might come from the development of real-time adaptive ANNs that can adjust to changing engine conditions and fuel properties, leading to optimized engine performance and reduced emissions. The exploration of ANNs in bio-diesel production techniques indicates a growing interest in applying ANNs beyond engine performance to encompass the entire biodiesel production and utilization cycle [95].

Further exploration is needed to improve the application of neural networks (NNs) in biodiesel-fueled compression ignition (CI) engines. Advancements in neural network structures, refined training techniques, and hybrid machine learning approaches could provide deeper insights into the dynamics of CI engines. Combining these technological improvements with innovations in biofuel production will enable optimized engine performance, reduced emissions, and a more sustainable energy future [96–98].

6.3. Actionable Recommendations for Future Research

To maximize the potential of ANNs in biodiesel engine technology, future research should address the following areas:

- Real-time adaptive ANNs: design ANN models capable of adjusting to changes in engine conditions and fuel properties in real time, improving operational efficiency and reducing emissions.
- Lifecycle optimization: expand ANN applications beyond engine performance to encompass biodiesel production, blending, and supply chain optimization for a holistic approach.
- Hybrid approaches: integrate ANNs with emerging techniques, such as deep learning, reinforcement learning, and big data analytics for more accurate and scalable solutions.
- Sustainability metrics: incorporate environmental impact assessments into ANN models to evaluate the sustainability of biodiesel use across its lifecycle.

7. Conclusions

In conclusion, the application of artificial neural networks (ANNs) in biodiesel-fueled diesel engines highlights their significant potential in improving engine performance and reducing emissions. ANNs excel in predicting complex relationships between biodiesel blends and engine parameters, contributing to advancements in renewable energy adoption within the automotive sector. Despite challenges in data collection, model training, and generalization, emerging trends, such as integrating ANNs with big data and advanced algorithms, are driving improvements in modeling precision and reliability.

The application of artificial neural networks (ANNs) in biodiesel-fueled diesel engines underscores their significant potential for improving engine performance and reducing emissions. Key findings include:

- Enhanced prediction and optimization: ANNs effectively model complex relationships between biodiesel blends and engine parameters, enabling the better prediction of performance metrics and emission characteristics.
- Emission reduction potential: ANN models demonstrate their utility in optimizing engine parameters to mitigate harmful emissions, particularly nitrogen oxides (NO_X), while maintaining overall efficiency.
- Integration with advanced technologies: the combination of ANNs with big data analytics and advanced algorithms has shown promise in improving model accuracy and reliability across diverse engine configurations.
- Hybrid model effectiveness: studies reveal that integrating ANNs with hybrid techniques, such as genetic algorithms and fuzzy systems, enhances optimization and adaptability under variable conditions.

Future research should prioritize hybrid ANN models, combining techniques like genetic algorithms and deep learning to enhance predictive accuracy and optimization. Developing real-time adaptive systems will enable dynamic adjustments to engine conditions, while comprehensive cost analyses will further establish the economic feasibility of ANN-optimized biodiesel engines.

The integration of ANNs in biodiesel engines represents a vital step toward environmentally sustainable automotive solutions, underscoring the role of artificial intelligence in fostering innovative, efficient, and eco-friendly energy systems.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Networks
BPNN	Back Propagation Neural Network
RBFNN	Radial Basis Function Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
BTE	Brake Thermal Efficiency
EGT	Exhaust Gas Temperature
CO	Carbon Monoxide
HC	Hydrocarbons
NO_X	Nitrogen Oxides
PM	Particulate Matter
BSFC	Brake Specific Fuel Consumption
BSEC	Brake Specific Energy Consumption
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
MAP	Mean Absolute Percentage
MSRE	Mean Squared Relative Error

MEP	Mean Error Percentage
MRE	Mean Relative Error
FTDFRNN	Fuzzy Time Delay Fully Recurrent Neural Network
CI Engine	Compression Ignition Engine
WCO	Waste Cooking Oil
HME	Honge Methyl Ester
JME	Jatropha Methyl Ester
RSM	Response Surface Methodology
HRR	Heat Release Rate

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