Type of contribution:
Editorial
Research Paper
Case Study
▶ Review Paper
Scientific Data
Report of Tech. Application

mesi
e-issn. 2798-5245

Mechanical Engineering for Society and Industry
Vol. 4, No. 3 (2024) pp 513-534
Special Issue on Technology Update 2024
https://doi.org/10.31603/mesi.12742

A Review of the artificial neural network's roles in alternative fuels: Optimization, prediction, and prospects

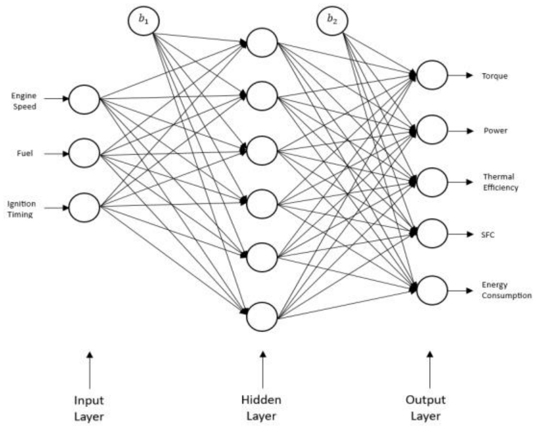
Hendry Y. Nanlohy[1,a], **Susi Marianingsih**[2,b], **Fitri Utaminingrum**[3]

[1] Department of Mechanical Engineering, Jayapura University of Science and Technology, Jayapura, 99351, **Indonesia**
[2] Computer Vision Research Group, Faculty of Computer Science and Management, Jayapura University of Science and Technology, Jayapura, 99351, **Indonesia**
[3] Computer Vision Research Group, Faculty of Computer Science Brawijaya University, Veteran 12-14, Malang, 65145, **Indonesia**

✉ hynanlohy@gmail.com[a], ssmarianingsih@gmail.com[b]

This article contributes to:

7 AFFORDABLE AND CLEAN ENERGY
SUSTAINABLE DEVELOPMENT GOALS



Highlights:

- ANNs accurately in modeling, optimizing, and predicting the performances of alternative fuels
- ANNs enhance fuel efficiency and reduce emissions by optimizing combustion parameters.
- ANNs effectively support sustainable energy development and the shift to a green economy.

Abstract

Artificial Neural Networks (ANN) are increasingly employed in alternative fuels to enhance efficiency and mitigate environmental impacts. This article comprehensively reviews the application of ANNs in modeling, optimizing, and predicting the properties of various alternative fuels. ANNs excel at capturing the complex non-linear relationships inherent in these fuels' physicochemical properties and combustion processes, which can be challenging to forecast using traditional mathematical models. By leveraging ANNs, combustion parameters can be optimized, thereby improving fuel efficiency, reducing exhaust emissions, and enhancing overall engine performance. Additionally, this research explores the effective use of ANNs in forecasting engine performance and emissions for alternative fuels, while also addressing key challenges, including the need for high-quality data and the optimization of algorithms for better accuracy. Additionally, the article considers the future potential of ANNs in supporting sustainable energy development and facilitating the transition to a green fuel economy. With advancements in computing technology, ANNs are anticipated to remain a vital instrument in the progression of alternative fuel research and its associated applications.

Keywords: Artificial neural networks; Accurate prediction; Alternative fuels; Engine performance; Exhaust emission

Article info
Submitted: 2024-12-01
Revised: 2024-12-20
Accepted: 2024-12-22

Publisher
Universitas Muhammadiyah Magelang

1. Introduction

The global energy crisis [1], [2], coupled with escalating concerns regarding climate change [3], [4], has necessitated a concerted effort among researchers and engineers to explore alternative fuels that are both environmentally friendly and sustainable [5]–[8]. Prominent alternative fuels such as ethanol, methanol, butanol, CNG, LPG, hydrogen, and biodiesel present promising solutions to mitigate addiction to fossil fuels (see **Figure 1**) and also decrease greenhouse gas emissions [9]–[14]. Nevertheless, a significant challenge in developing and deploying these alternative fuels lies in the intricacies of their physicochemical properties [15], [16] and combustion

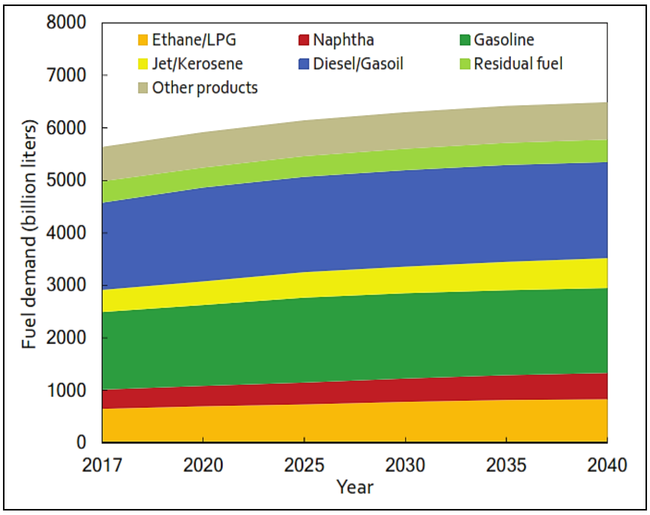


Figure 1. Projection of worldwide demand for refined fuels products from 2017 to 2040 [6], [17]

dynamics [18], [19], necessitating innovative methodologies for thorough understanding and optimization [20], [21].

Artificial Neural Networks (ANN) a subset of artificial intelligence (AI), has surfaced as highly effective tools for addressing complex non-linear [22]–[25]. ANNs possess the capability to capture intricate relationships that traditional mathematical models often struggle to predict, particularly in the realm of alternative fuels [26]–[30]. The integration of ANNs facilitates enhanced modeling of fuel properties, optimization of combustion parameters, and accurate forecasting of engine drive system efficiency and exhaust profile [31], [32]. Within this paradigm, ANNs proffer considerable advantages, including the ability to process variable or limited datasets while concurrently enhancing fuel efficiency [33], [34] and minimizing environmental impacts [35]–[37].

Numerous studies have demonstrated the successful application of ANNs to predict alternative fuels' behavior in combustion engines, focusing on aspects such as energy efficiency and exhaust emissions [38]–[41]. The use of ANNs effectively optimizes critical combustion parameters, including fuel-air ratios, injection pressure, and combustion duration [42], which are pivotal in enhancing engine performance and curbing harmful emissions. This optimization becomes increasingly essential given the distinct characteristics of alternative fuels compared to conventional fossil fuels, often necessitating specific adjustments to the combustion system to realize optimal performance [43].

However, deploying ANNs in the context of alternative fuels is not devoid of challenges. One of the primary hurdles involves the necessity for high-quality data to train the neural network [44], ensuring accurate predictions [45], [46]. Additionally, optimizing ANN algorithms is crucial to minimize errors [47] and enhance prediction accuracy [48], mainly when working with highly variable data [49], [50]. Ongoing efforts are focused on overcoming these challenges, particularly through utilizing advancements in computing technology and sophisticated algorithm optimization techniques. As these technologies continue to evolve, it is anticipated that ANNs will remain pivotal in the research and development of alternative fuels. Their capacity to manage complex data and deliver precise predictions positions ANNs as an invaluable resource in transitioning towards a green fuel economy and sustainable energy solutions. This paper intends to present a comprehensive review of ANNs' applications in various types of alternative fuels, highlighting achievements while addressing future challenges and opportunities.

2. Material and Methods

2.1. Research Approach

This study is a comprehensive literature review on applying Machine Learning (ML) methods in bio-oil research, with a special focus on using ANN. This study will identify, classify, and analyze ML applications in various stages of bio-oil production, including the transesterification process and physicochemical properties analysis. The materials and methods section provides details on the data sources, search strategies used to find relevant articles, criteria for selecting studies included in the review, the total number of studies incorporated, as well as the statistical approaches or methods used for analysis.

2.2. Data Collection

A comprehensive critical review of relevant literature was performed using reputable journals accessed through a single academic database, ScienceDirect (https://www.sciencedirect.com/). The focus was primarily on Elsevier journals indexed in Scopus and WoS, ensuring a comprehensive and high-quality analysis of the existing research. The selected articles include recent studies on

ML applications, especially ANN, in bio-oil and renewable fuel research. The literature will be selected based on keywords such as "bio-oil", "machine learning", "artificial neural networks", "transesterification", "real-time monitoring", "physicochemical properties" "engine performances", and "exhaust emission". Studies focusing on modeling, controlling, and optimizing bio-oil processes will be prioritized. Furthermore, the following criteria were established to refine the discussion and ensure a focused review. Only selected articles were included, and those deemed outside the scope were excluded based on the following conditions:

a. Articles published in discontinued journals or those found to lack a rigorous peer-review process;
b. Articles not referenced in the original research paper and inaccessible;
c. Articles that do not examine the role of artificial neural networks (ANN) in relation to engine performance and emissions using alternative fuels; and
d. Articles that mention ANN in the abstract and body text but do not provide substantial evidence of its significance in the methods and results.

This systematic approach ensures the discussion remains focused and anchored in credible research findings. Table 1 presents a detailed overview of the limitations of selecting articles from the ScienceDirect database, highlighting specific challenges and criteria that prior studies have identified [51]. These limitations may include issues such as accessibility, publication bias, and the specificity of search parameters.

Table 1. Limitations of article selection

No	Article selection	Limitations
1.	Database	ScienceDirect
2.	Search within	Article title, abstract, keyword
3.	Search document	ANN, alternative fuels, engine performance, exhaust emission
4.	Type of access	All (All Open Access, Gold, Hybrid Gold, Bronze, Green)
5.	Year	2012-2025
6.	Subject area	Alternative fuels, Bio-oil, machine learning, "artificial neural networks, and transesterification, real-time monitoring, physicochemical properties, engine performances, and exhaust emission.
7.	Document type	Article
8.	Publication stage	Final
9.	Source title	All (not specified)
10.	Keywords	All (not specified)
11.	Affiliation	All (not specified)
12.	Funding sponsor	All (not specified)
13.	Country	All (not specified)
14.	Source type	Research article (Journal)
15.	Language	English

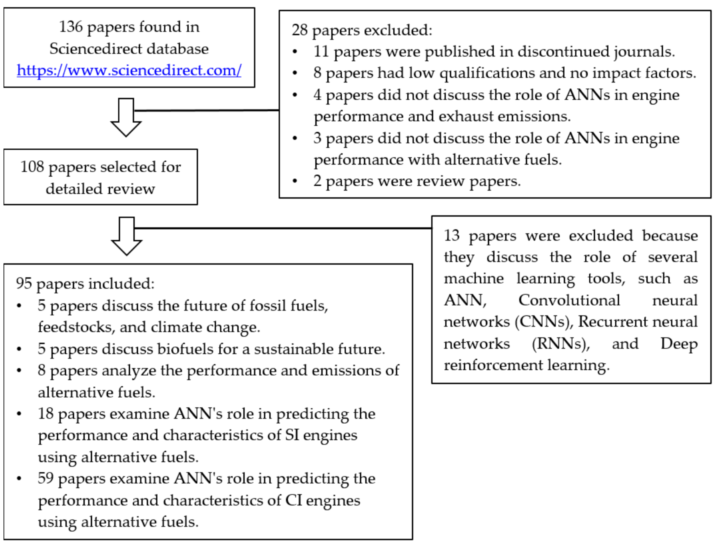


Figure 2. Literature selection and data analysis process

Meanwhile, Figure 2 provides a comprehensive illustration of the methodology employed for literature selection and the data analysis process, outlining each step to ensure thorough evaluation and synthesis of the relevant literature. This visual representation facilitates a clearer understanding of how the research was conducted and the rationale behind the chosen methods. Furthermore, Figure 3 shows a classification of ANN models showing that multi-layer perceptron, extreme learning machine, and self-organizing map methods have been used in alternative fuel research. Furthermore, the classification of artificial neural network (ANN) models shows that multi-layer perceptron, extreme learning machine, and self-organizing map methods have been used in alternative fuel research, as presented in **Figure 2**.

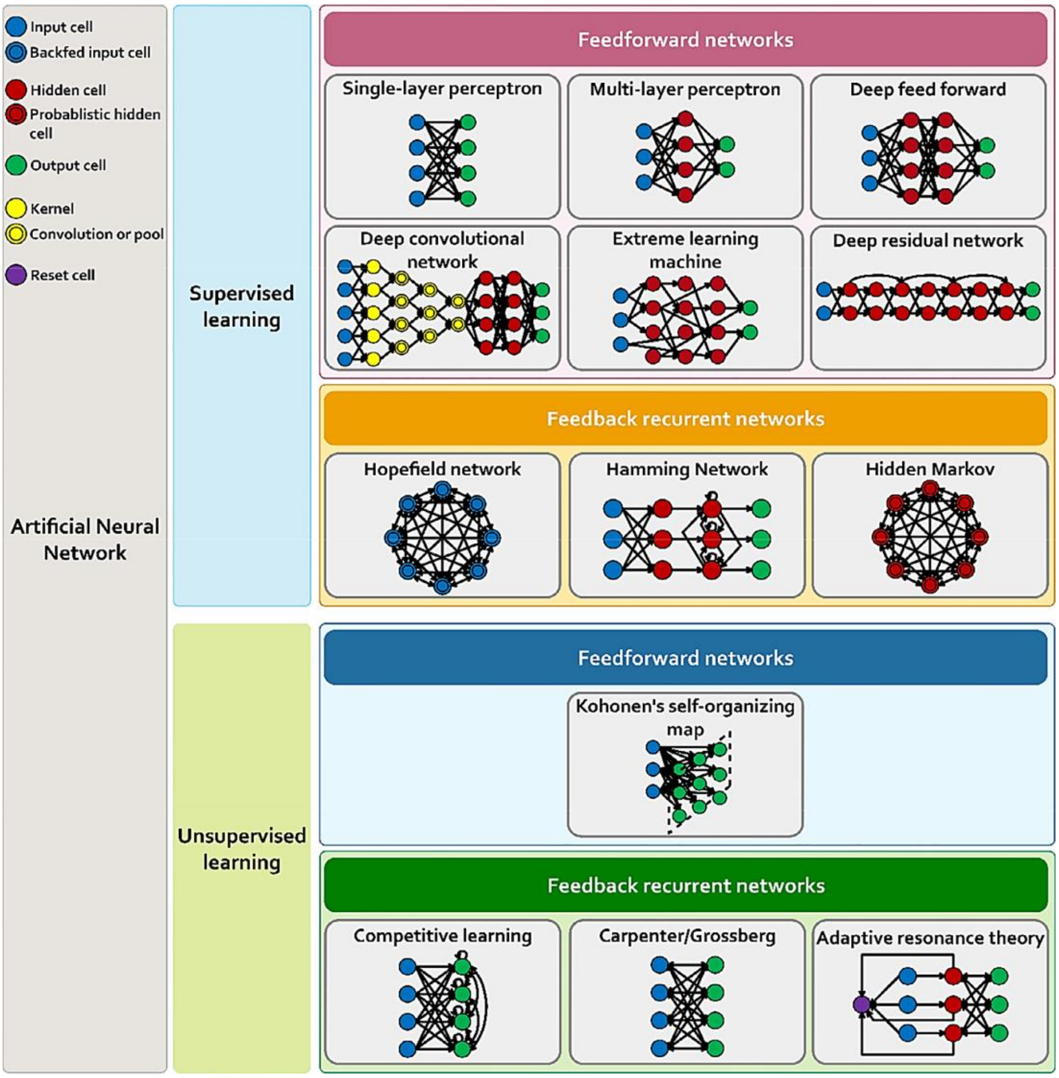


Figure 3. ANN model classifications highlighting the use of multi-layer perceptron, extreme learning machine, and self-organizing map methods in alternative fuel research

3. Results and Discussion

3.1. Alcohol Group (Ethanol, Butanol, and Methanol)

3.1.1. Ethanol

Several studies carried out an in-depth study aimed at forecasting the act metrics of a mono and four-chamber gasoline engine under different ignition timing conditions [23], [33], [52], [53]. The research used a fuel blend of gasoline and ethanol, with a specific emphasis on a 50% ethanol mix. To accomplish this, they utilized an ANN, a computational method recognized for its ability to learn and replicate intricate patterns in data. To develop the ANN model effectively, the researchers collected experimental data under controlled conditions that simulated dynamic engine speeds and entire load operations. This dataset was the foundation for training and testing the ANN, ensuring the model accurately reflects real-world engine performance. The ANN architecture utilized a double-segment perceptron chain, particularly suited since capturing along relationships through inputs-outputs. The model was trained using a standard back-propagation (BP) algorithm tailored for applications in spark ignition engines. Additionally, an optimizer from the quasi-Newton family, specifically the limited-memory broyden fletcher goldfarb shanno algorithm, was employed alongside the rectified linear unit activation function [54], [55]. This combination was crucial for evaluating the percentage error between the predicted results and experimental values. The researchers included critical parameters such as engine speed (measured in RPM), the type and ratio of fuel used, and ignition timing (angles) as inputs to the ANN. The model's outputs encompassed several key performance indicators, including torque; power, sfc,

η_{th}, also overall energy consumption. The study's findings underscored the effectiveness of the ANN method for predicting the SIE engine work has fueled by the BE50 blend. The results highlighted the minimal prediction errors, which were found to be approximately 0.003 for the training dataset and 0.002 for the testing dataset, reflecting high accuracy in the model's performance. Additionally, a robust correlation was observed between the predicted and experimental data, indicating that the ANN was able to replicate observed engine behavior closely. Overall, the ANN analysis revealed a favorable correspondence between the predicted data generated by the model and the actual measured values obtained during experimentation. This research demonstrates the potential of ANN in engine performance prediction and emphasizes its capability to reduce the necessity for extensive experimental validation significantly. Consequently, the developed model is an efficient and powerful tool for forecasting engine performance metrics and emission characteristics across various operational scenarios, especially when dealing with diverse biodiesel blends.

3.1.2. Butanol

Numerous studies have thoroughly examined the impacts of cyclic variability on the engine works and tailpipe pollutants, specifically when using both pure diesel and diesel-butanol fuel blends [56], [57]. They conducted their study on the concentration of n-butanol in the fuel blends was adjusted from 3% to 15% in steps of 3%. The researchers developed a neural network model with one hidden layer consisting of 11 neurons. The regression values for the model are 0.9788, and 0.879 for the practice, validation, and test modes. Additionally, the error for the training, validation, and test datasets ranged between 3.9592 and 8.7095. The results show a strong alignment with experimental data, reflecting a high level of accuracy. One of the pioneering studies on the effectiveness of ANN models for forecasting engine work and emitted pollutants in alcohol-gasoline engines [57], [58]. The study focused on evaluating key performance indicators such as brake power, torque, bsfc, ηth, and exhaust gas. The insertion parameters for the back-propagation pattern included crankshaft pace (rpm) around 1,000 to 5,000 rpm. The model's objective was to predict exhaust emissions and overall engine performance accurately. The study determined the top hidden layer model by adjusting the some of neurons, experimenting with different activation functions, and testing various training algorithms. However, the study did not clarify whether the input-output data were normalized, leading to the presumption that such normalization was not implemented. The activation functions evaluated included tansig and logsig, while the training algorithms examined encompassed trainlm, traingdx, trainscg, and trainrp. To assess the effect on the correlation coefficient (R), the value of neurons in the deep layer was varied between 19 and 23. In this study, 80% of the total real dataset, comprising 410 data points, was utilized for practice, while the remaining 20% was reserved for trial. Additionally, both the root mean square error (RMSE) and mean relative error (MRE) were computed to assess the work of the prediction pattern. The findings showed that the ANN model with 20 hidden neurons, using a sigmoid with the trainlm algorithm, provided the most precise predictions with R-value is 0.9989. The correlation coefficients for power, torque, ηth, volumetric efficiency, BSFC, and emissions were 0.999, 0.995, 0.981, 0.985, 0.986, 0.994, 0.987, also 0.984. The mean relative error (MRE) of the predictions ranged between 0.46% and 5.57%, with low RMSE values, further highlighting the model's accuracy.

Meanwhile, previous researcher [59] used bp-ANN to estimate key work indicators for a methanol-fueled 4 chamber of SIE. The model's input utilized spin force, crankshaft RPM, combustion feed rate, nlet chamber thermal state, and engine coolant intake heat level as input factors. It predicted SFC, effective work and pressure, along with combustion outlet temperature (COT). The rpm was set around 1200 to 4400 rpm in 300 rpm increments, while torque ranged between 5 and 70 N·m. A conservative approach was taken by predicting each output parameter separately, resulting in the development of four distinct ANN models. The study leveraged the logistic sigmoid (logsig) activation function and tested both single and dual hidden layer structures. The training algorithms assessed included trainlm (Levenberg-Marquardt) and trainscg (Scaled Conjugate Gradient), while some neurons in the unknown sheet varied from 4 to 16. A 75:25 data division was implemented, with 44 data training and 11 tested. Additionally, it is worth noting that the authors applied a data normalization range of 0.1 to 0.9 for the input-output variables, which differs from the typical normalization range of 0–1 or −1 to 1. While the choice of this normalization range was likely made to prevent saturation of the sigmoid function, though it was not explicitly explained., a condition that could hinder or completely stop its learning process, as discussed by Tarigonda [60] and Thangaraja [61]. The operational efficiency of the ANN pattern was assessed through RMSE, coefficient of determination (R^2), and mean absolute percentage error (MEP). The study identified the most effective topology and learning algorithms for predicting bsfc, power output (Pe), power output (APe), and exhaust temperature (Tex) as 5-5-5-4, 5-6-4, 5-7-4, and 5-7-4, respectively, with trainlm being utilized for all except APe, which employed trainscg. The R^2 values for testing and training all powertrain metrics are around 0.999. This approach offers a viable alternative to traditional predictive modeling techniques.

3.1.3. Methanol

In another investigation, Bathala et al. [55] and Sujin et al. [62] created ANN models to predict BSFC, carbon monoxide, hydrocarbon, and air-fuel ratio (AFR) for a SIE running on both petro-fuel and methyl-alcohol fuels. The researchers adjusted revolution rate (rpm) and torque, similar to the earlier work [63]. The independent variables included rpm, torque, and fuel, while the outputs were the specific engine performance and emission parameters. Notably, each output was treated separately, leading to the creation of four distinct models for each output by varying the number of neurons from 5 to 15 to determine the optimal neuron count that minimized the mean square error. The prediction performance was assessed using RMSE, MEP, and R^2. The results showed that the most precise predictions with the train algorithms, employing web configurations, and the R^2 values for practice and trial in predicting engine work were 0.9675, 0.9823, 0.9901, 0.9945, 0.9438, 0.9789, 0.9854, and 0.991.

Furthermore, Taheri-Garavand and Cheng [40], [64] carried out a study using a bp- ANN model to forecast the SIE works and pollutant with ethanol-gasoline. The model's input variables included different fuel combinations, with ethanol content ranging from 0% to 20% in 5% increments, along with engine speeds and loads set at 25%, 50%, 75%, and 100%. The output parameters of engine's works kincluded several training algorithms, including trainlm, traingdx, trainrp, and trainscg, were investigated to optimize the model's elevation coefficient (R) and mean squared error (MSE). The datas of neurons in each layer was adjusted between 15 and 35 to determine the most effective configuration. The input data were normalized to a area of -1 to 1 to warrant fair contribution from any fickle. Ninety percent of the 50 trials were used for practice, while the persisting samples were held back for testing. The study identified the optimal architecture as a two-hidden layer setup of 5-25-25-7, which achieved the highest correlation coefficient of 0.99998. The correlation coefficients for engine works obtained from the ANN model were 0.99, 0.96, 0.98, 0.96, 0.90, and 0.71, respectively.

3.1.4. Gasoline-methanol and ethanol

In a related study, Udaybhanu [57] and AlNazr [65] investigated the work of a SIE with gasoline-methanol and ethanol engine fueled with the alcohol content reaching up to 15%, alongside unleaded gasoline. An ANN was employed to assess its predictive capabilities concerning powertrain metrics, including rotational force, mechanical output, and sfc. The model developed in the study aimed to identify the ideal methanol-to-ethanol ratio for maximizing engine torque and power while minimizing specific fuel consumption (SFC). Engine speeds were tested from 1300 rpm to 3000 rpm, and the ethanol and methanol blend ratios were set at 5%, 10%, and 15% by volume. For example, a blend of 5% methanol and 10% ethanol was denoted as M05E10. The model's input variables included engine RPM and fuel mixture ratio, with the goal focusing on engine performance metrics. Three ANN models were created using these outputs, and the input data were normalized to a range of 0 to 1. Following the 85:15 training and testing data split for model evaluation. Performance was assessed using metrics like R, R^2, RMSE, and direction accuracy (DA) value near to one suggest strong alignment between predictions and actual system behavior. The optimal network architectures for predicting torque, brake power, and BSFC were found to be 3-10-1, 3-10-1, and 3-18-1, respectively, using the tansig transmission part. The recorded R and DA values for these metrics were 0.9906 and 0.889 for torque, 0.9970 and 1.0 for brake power, and 0.9312 and 0.889 for BSFC. The study focused on predicting performance metrics for two types of HCCI engines: SI and CI-converted engines, both running on ethanol and butanol. The analysis was performed using conventional multilayer perceptron (MLP) ANN models and long short-term memory neural network models.

Moreover, a nearly identical study by Bichitra [66] about the butanol with powered engine variable compression ratio (VCR) engine using copper oxide (CuO) with a single-cylinder retrofitted with a variable valve timing (VVT) engine cylinder head, produced several output parameters, including Pmax, and gas emissions, as well as indicated thermal efficiency. For the butanol engine, the dataset was split at 70:30 for training and testing, but normalization details were not specified. Both ANN models were evaluated, and the feedforward model was also tested on the CIE using a logsig activation function. The rationale for not assessing the RBF ANN in this particular instance remains unclear. The ANN predictive capability was assessed using R^2, RMSE, and mean percentage error. In terms of accuracy, the R^2 value for the FF ANN model during testing was higher than that of the RBF ANN, while the RBF ANN outperformed the FF ANN during training. For the CIE, the R^2 varied from 0.89 to 0.94 for the output parameters. The study definite that the models could estimate HCCI motor work metrics with an inaccuracy margin below 5%.

3.2. Biodiesel Group

Biodiesel production is categorized based on feedstock, transesterification technique, mode of operation, reactor, and process intensification (See **Figure 4**). Feedstocks come in four generations, ranging from edible vegetable oils to genetically engineered microalgae. Newer generations, such as waste oils and microalgae, are more sustainable and environmentally friendly. Transesterification techniques include using homogeneous catalysts (soluble acids or bases), heterogeneous catalysts (solid and separable), and non-catalytic methods that utilize supercritical alcohol without a catalyst. Each technique has advantages and challenges, especially related to efficiency and cost. Production is carried out in batch or continuous modes. Batch mode is suitable for small-scale production, while continuous mode is more efficient for large-scale production with reactors such as plug flow and continuous stirred tanks. Intensification processes use technologies such as microwaves, ultrasound, and membranes to speed up reactions and save energy, making biodiesel production faster and more efficient.

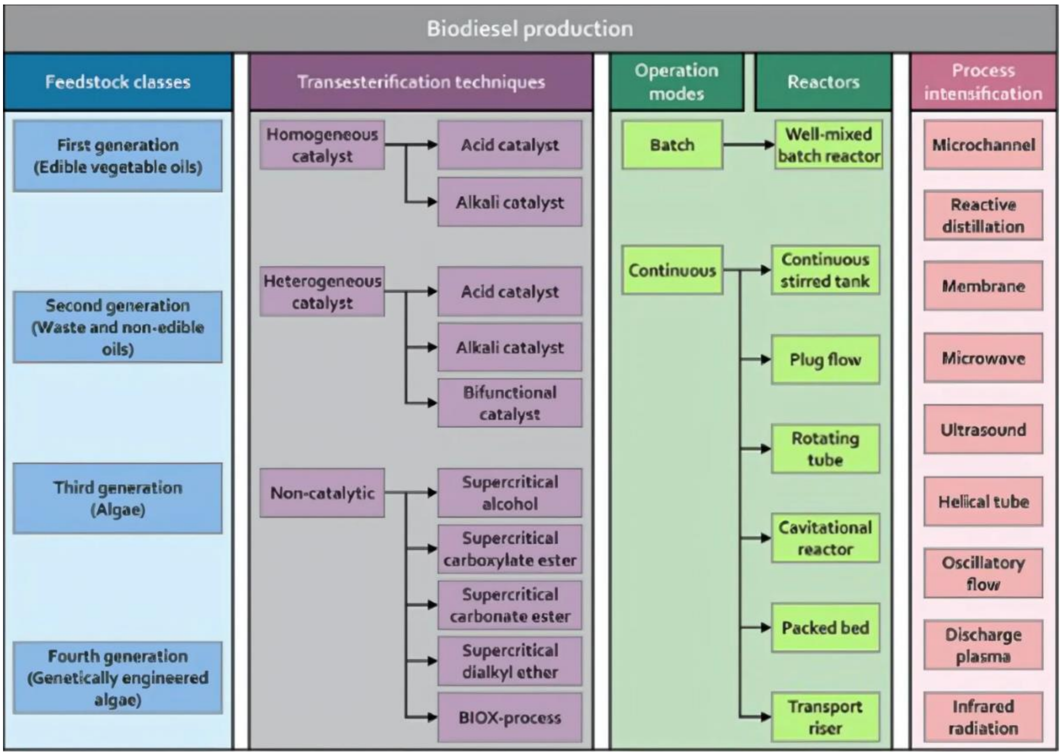


Figure 4. Classification of strategies for biodiesel production [17], [67]–[69]

3.2.1. Crude glycerol and diesel

In a late observation, various studies thoroughly evaluated the predictive capabilities of ANN through various engine performance indicators and pollutant gas traits [70]–[72]. The research centered on analyzing BTE, EGT, BSEC, and emissions such as HC, CO_2, CO, NO, O_2, and soot. The study utilized blends of crude glycerol and diesel oil in a DIE-CIE. The fuel blends content in the fuel was adjusted between 10% and 25%, increasing by 5% increments. Engine load was progressively increased from idle to maximum capacity in 25% steps. The study also examined the impact of two fuel injection timings (FIT) and two fuel injection pressures (FIP) — 250 bar and 280 bar — with timing settings of 20° and 24° bTDC. Two distinct ANN models were developed: one to predict emissions and the other to assess motor work. The emissions model included an unknown sheet with 18 neurons, while the performance model had two unknown sheets, each consisting of 12 neurons. The network architecture was optimized by adjusting the neurons between 5 and 25, choosing the best configuration based on the minimization of mean squared error, which was used as the objective function. In addition, the models' predictive capabilities were thoroughly evaluated using a range of conventional and advanced accuracy and deviation metrics, such as RMSE, coefficient of determination, and uncertainty index. The findings revealed a high level of predictive accuracy, highlighting the models' effectiveness in predicting emission characteristics and engine performance. These results affirmed the reliability of ANNs to this context.

3.2.2. Waste vegetable cooking oil

On the other side, El-Adawy et al. [73] conducted a study to forecast the drive system efficiency and exhaust profile by a blend of waste vegetable cooking biodiesel and pure diesel. The research involved a CIE operating at various speeds, utilizing a back-propagation artificial neural network (ANN). Key performance metrics, such as torque and brake-specific fuel consumption (BSFC), were examined, along with emissions of hydrocarbons and carbon monoxide. The ANN model incorporated input variables including engine speeds ranging from 1200 to 3600 rpm and biodiesel blend ratios varying from 0% to 50% in 10% increments. A specific unknown sheet standard was employed, with different activation functions (logsig and tansig) and training algorithms like trainlm, traingdx, trainrp, and trainscg being tested. The sum of neurons in the unknown sheet was adjusted between 22 and 28. The model's inputs and outputs were normalized to a range of -1 to 1, with the objective function being the mean squared error (MSE), set at 0.00001, to estimate both practice and trial work. The dataset was divided, with 80% used for training and the remaining 20% for testing and validation. The sensitivity analysis showed that the most effective ANN model utilized 20 neurons, and this configuration resulted in an R of 0.996.

In addition, to gain insights into the impact of artificial neural networks (ANN) in the work of compression ignition engines fueled by WCO, then previous studies [74], [75] examined the impacts of fuel spray timing on different emissions and powertrain metrics. Their study utilized a stationary CI engine fueled by a blend of WCO and diesel. The study employed ANN to predict critical parameters of engine performance, exhaust gases, smoke. Three different network models were assessed, each focusing on either individual prediction of emissions and engine performance or a combined approach. The tested WCO-to-diesel blend ratios were 5:95, 10:90, 15:85, and 20:80. The compression ratios considered were 14 and 16, while injection timing was adjusted from 1° to 4°. The data were normalized by scaling the inputs to a range of -1 to 1, ensuring that all variables contributed equally to the network. The learning process configurations, such as trainrp was applied to all models, with performance evaluated using Mean Squared Error as the cost function. The optimal part of neurons work indicator was determined to be 24, achieving an MSE of 0.015, while the emission model optimally utilized 22 neurons with an MSE of 0.013. For the combined model, 24 neurons were also deemed optimal. Notably, the trainlm algorithm demonstrated the shortest training epochs compared to other algorithms across all models. The Mean Relative Error (MRE) and prediction accuracy were employed as statistical measures to assess the models' performance. The findings indicated that the individual models produced superior predictions compared to the mixed exemplary, which exhibited kind of greater MRE and reduced certainty in its predictions.

3.2.3. Jatropha, Karanja, Mahua, Coconut oil and Neem

Furthermore, Javad et al. [76] also did the same thing, using a feed-forward ANN model to utilize predicted outputs of the predicted powertrain efficiency and exhaust profile for a jatropha ethyl ester diesel mixture in a direct injection compression ignition (DI-CI) engine. The performance metrics analyzed include brake-specific fuel consumption (BSEC), brake thermal efficiency (BTE), and exhaust gas temperature (EGT). The emission parameters considered in the study are CO_2, CO, HC, NOx, and smoke. The input parameters for the model include compression ratio (CR), static injection timing (SIT), fuel injection pressure (FIP), engine load, and fuel mixture ratios. These ratios were adjusted to various blends of jatropha methyl ester to diesel: 10%, 30%, 50%, 70%, and 90%. The data compilation adhered to a standard distribution, allocating 70% for training, 15% for testing, and 15% for validation. All input parameters were normalized within a range of 0 to 1. To determine the optimal training algorithm, a single hidden layer network was trained with several algorithms with the values of neurons was adjusted between 10 and 45, in increments of five, with an additional configuration using 28 neurons. Sensitivity analysis indicated that the configuration of 28 neurons resulted in the lowest mean squared error (MSE), and this configuration was consistently applied across the various training algorithms. The MSE was set as the stopping criterion at a threshold of 0.001. The performance of the developed models was evaluated using the correlation coefficient (R), mean squared error (MSE), and mean absolute percentage error (MAPE). The results indicated that the train algorithm delivered the lowest MAPE and the highest accuracy, as measured by R, for both the training and testing datasets. The forecast precision for the training data across the outputs was as follows: BTE (100%), BSEC (99.51%), EGT (99.01%), CO_2 (98.06%), CO (90.89%), NOx (87.83%), HC (91%), and smoke (88.12%).

Similarly, Sayyed et al. [77], Uslu [78], and Fangfang [79] studied the role of various FAMEs oil (Jatropha, Karanja, Mahua, and Neem) diesel blends on drive system efficiency and pollution signature in diesel engine. The FAMEs oil diesel blends compositions were set at 10%, and 90%, referred to as B10, and B90. They created six different ANN models to evaluate the influence of various input parameters on multiple output parameters. Following the identification of significant statistical errors with IP in the first model, additional networks were introduced to augment the study. The 3rd network used the same inputs as the first model but excluded IP from the output. The 4th web retained the inputs from the 2nd model but removed IP from the outputs, while the fifth network mirrored the inputs of the first model and included outputs from both the first and second models. The models employed the normalized input/output input features between 0 and 1. Training algorithms included trainscg and trainlm, with 6 to 9 neurons in the hidden layer. Unfortunately, the specific training and testing points were not provided.

The ANN models' performance was evaluated using RMS, R^2, and error metrics. The optimal combinations of the learning algorithm and number of neurons for each network were identified as follows: trainlm-6 for the first network, trainscg-7 for the second, trainlm-5 for the third, trainscg-7 for the fourth, and trainscg-8 for the fifth model. It was determined that the fifth model was adequate for predicting drive system efficiency and exhaust profile, as its output error values closely matched those of the first and second models. Despite the development of five distinct networks, a more meaningful evaluation could have been achieved by analyzing the network outputs individually, focusing on powertrain metrics separate from emission parameters, as well as a model integrating all outputs concurrently.

Somes tudies [75], [80]–[82] carried out an in-depth study examining the impact of citronella oil and coconut oil ethyl esters on the drive system efficiency and tailpipe pollutants profile of diesel engine. They developed an ANN designed to predict BSFC, engine torque (ET), and emissions (CO_2, HC, NOx) using inputs like engine load, fuel type, and testing blends (pure diesel, B20, B40). The inference system featured a neural processing unit with eight neurons and normalized intermediate values 0.2 and 0.8. It was trained using the trainlm algorithm with MSE as the cost function, split into 85% training and 15% testing. The inference system achieved a correlation coefficient of 0.997. This study highlights vegetable oil ethyl esters as a viable alternative fuel and demonstrates the effectiveness of the thermal barrier and ANN modeling approach.

3.2.4. Crude coconut, Palm, and Soy biodiesel

Sharma [83] and Bajwa et al. [74] conducted a study to examine the predictive capabilities of ANN on nine engine outputs influenced by various biodiesel blends in a compact diesel powertrain. Fuels tested were crude coconut, palm, soy biodiesel, a 50% palm-diesel blend (B50), and pure diesel. The model predicted outputs such as all carbon emissions and NO. While data were normalized, details of the process were unspecified. The dataset was split 80:10:10 for training, testing, and validation, using ten neurons in the hidden layer. The tansig-purelin configuration achieved the lowest MSE. The ANN model exhibited strong performance, with high regression (R) values of 0.984, 0.987, 0.981, 0.985, 0.942, 0.977, and 0.939 for CO, CO_2, and NO. However, the R values for unburned hydrocarbons (UHC) and CAD HRRmax were lower, at 0.552 and 0.558, indicating a need for improved input parameters to better capture the engine's behavior and predict its output responses. This finding emphasizes the necessity for further refinement in model inputs to enhance predictive accuracy.

Thangaraja et al. [84] and Bahattin Işcan [85] carried out a significant study to evaluate the effectiveness of ANN in predicting the performance and emissions of methyl ester fuel blends from vegetable and non-vegetable fried oils. For training, blends B25, B50, and B75 were tested at a constant 1500 rpm with varying loads. Inputs included brake power and blend type, while outputs were BSFC, BTE, CO, NOx, HC, and smoke. The model used a single hidden layer with tansig for the hidden layer and purelin for the output. Training used the trainlm algorithm, though data normalization and neuron count were unspecified. The R values were 0.9998 for the outputs, except 0.998 for CO. Unfortunately, the article did not provide this crucial information, making it unclear whether the predicted results were compared to the actual experimental data from previous research [62], [86], [87] for blends B20, B40, B80, and B95 derived from karanja and algae Oil.

3.3. Hydrogen-based Fuel

Reddy [88] clearly showcased the efficacy of various transfer functions like tansig, logsig, and purelin, for predicting engine work indicators (BTE, BSFC, CO, NOx, HC, and EGT) in a diesel engine. The study tested neuron counts from 1 to 25, using engine load and hydrogen flow rate as inputs. The trainbfg algorithm with eight neurons and the tansig-tansig transfer function achieved the highest regression values for the all-engine work indicators with R values around 0.9997. Moreover, Tayarani and Paykani [89] analyzed emissions from a ICE running on hydrogen using a bp-ANN model with one neural processing unit. The model used inputs like crankshaft speed, throttle valve angle, intake air volume, intake pressure, pulse width modulation (PWM), output power, spark timing, temperatures, combustion ratio, and tailpipe heat to exhaust gas emissions. With eight computational nodes in the neural processing unit and the tansig node response function, the model was trial using efficient backpropagation optimizer. The MSE was used as the objective function in this study. Around 1400 data points were designated for training, and a smaller set of 50 data points was set aside for testing. The model's prediction accuracy was thoroughly assessed, showing that the artificial neural network (ANN) effectively forecasted emission characteristics with a remarkable average RMSE of under 4%. These results clarify previous studies investigating CI engines' drive system efficiency and exhaust profile fueled by hydrogen with a mixture of prosopis juliflora [90].

In another important study by Shirneshan et al. [91], designed a single-layer ANN framework was created to predict how engine speed and throttle position affect engine work and emissions. The investigation comprehensively assessed various training algorithms, conclusively identifying the trainlm learning algorithm as the most effective. A substantial dataset consisting of 1400 entries was employed for training, with 50 data points allocated for testing; it is noteworthy that the data scaling was not reported. The analysis rigorously included several loss functions, including the MSE, applying the tansig function to the hidden layer and purelin to the output layer. By adjusting the number of neurons in the hidden layer, the optimal configuration of 10 neurons was decisively identified. Although regression metrics were not presented, the model received thorough assessment through other robust statistical measures, including average RMSE, average error (numerical and percentage), and standard deviation. The ANN model demonstrated robust predictive performance, with an average RMSE of under 3%.

Khan [92], Prajapati [93], and Liang [94] compellingly explored the efficiency and pollutant emissions in a CI engine in dual fuel mode with hydrogen using an ANN framework. They designed an ANN architecture with two unknown sheets, defining load and hydrogen injection duration as the input parameters, while targeting NOx, filtered smoke number as the output variables, and BTE. The input-output data were systematically normalized within a range of 0.1–0.9%, with 80% of the data designated for trial and the remaining 20% allocated for testing and validation. The study utilized a logsig-tansig configuration for the activation functions and, through rigorous heuristic analysis of MSE minimization, determined that each hidden layer should consist of 15 neurons. Additionally, a predictive uncertainty evaluation was performed using U2 error measure to assess the reliability of the model's predictions. The study conclusively demonstrated that the use of ANN, supported by comprehensive evaluations, can provide a highly precise predictive model.

3.4. Compressed Natural Gas (CNG)

The research conducted by Ramachandran et al. [95] represents a significant contribution to the application of Artificial Neural Networks (ANNs) in predicting the performance and emissions of a CNG-diesel engine, exploring both single and dual hidden layer configurations. The study compared the performance of the trainlm and traingdx algorithms, testing various transfer functions and neuron counts. A 70:30 split was used for learning phase and evaluation with 220 datasets. The optimal network configuration was 2-22-9, using the trainlm algorithm and logsig activation, achieving high correlation values: brake power (0.9808), torque (0.9884), BTE (0.92897), BSFC (0.9838), exhaust temperature (0.9934), CO (0.9359), CO_2 (0.9964), NOx (0.95707), and O_2 (0.9705).

Meanwhile, other studies developed multilayer perceptron network to predict engine parameters included particulate matter, and hydrocarbons in a CNG-diesel dual-fuel system [96]–[98]. The model used input parameters like load, pulse width modulation, and natural gas fuel energy. With the log-sigmoid activation function and the trainlm algorithm, the study aimed to minimize MSE. The 385 data points were split into training, testing, and cross-validation sets

(70:15:15). Although data scaling was not specified, the model performed well with raw data. The optimal network structure, determined after testing various neuron counts for the two unknown sheet (ranging from 2 to 25 neurons), was identified as a 3–8–8–5 architecture. The prediction performance was assessed using the correlation coefficient (R) and the coefficient of determination (R^2), along with additional error metrics such as MSE, RMSE, and mean absolute percentage error (MAPE). The results are the same as those of the previous studies [99], [100] and confirm the ANN model demonstrated high effectiveness, achieving an overall R-value around 0.999. The R^2 values for all engine work indicators were exceptionally high, reaching 0.999997, 0.996662, 0.999471, 0.999475, and 0.999778, respectively. MAPE values were remarkably low, ranging from 0.045% to 1.66%, and the RMSE values for all engine performance and emission parameters remained consistently low.

3.5. Liquefied Petroleum Gas (LPG)

Tarigonda et al. [60] and Kara et al [101] ectively employed an ANN for simulation the performance of a four-stroke gasoline engine running on liquefied petroleum gas (LPG), aiming for accurate predictions of motor efficiency and tailpipe pollutants. The model used engine speed and fuel type as input parameters, while the outputs included BSFC, efficiency, exhaust and engine body temperatures, along with exhaust gas emissions and unburned hydrocarbons. The study thoroughly explored the effects of using one or two unknown sheet and experimented with different numbers of neurons in each layer. A robust dataset of 220 experimental data points was strategically divided, with 70% allocated for training and 30% for testing. The Levenberg-Marquardt (trainlm) algorithm served as the chosen training method despite occasional misinterpretations as the activation function. The MSE function was firmly established acting as the performance metric, and a variety of activation functions were thoroughly tested to ensure optimal performance.

Furthermore, to provide an unequivocal evaluation of the ANN model's predictive capabilities, additional statistical metrics such as MRE, RMSE, and the R were incorporated. Notably, the study refrained from specifying the most effective topology, nor did it clarify if multiple topologies were reported in the prediction results. The correlation coefficients (R) for the output parameters demonstrated exceptional performance, yielding values of 0.9819 for BSFC, 0.9858 for efficiency, 0.899 for exhaust temperature, 0.9017 for engine body temperature, 0.9854 for NOx, 0.934 for CO_2, 0.9861 for CO, 0.9477 for O_2, and 0.9882 for UHC. The RMSE values remained consistently under 4% for all parameters, except for tailpipe pollutants temperature and all carbon emissions. Additionally, the MRE values were approximately 5% for the majority of the predicted output parameters, suggesting that the limited validation samples may have caused slight variations in the results. In addition, an ANN model was created to predict the diesel engine output and emission profiles running in LPG-integrated bi-fuels operation [102]. The model took load and LPG flow rate as input parameters, while the outputs included engine output parameters and emission profiles. This model was established with a single hidden layer, employing the logistic sigmoid function for dual layers secret and resultant data layers, and utilized MSE as its loss function. The neural layer configuration range two to twenty, alongside the dataset segmented into training (75%), validation (15%), and testing (15%); unfortunately, the study did not address whether data normalization was applied. The optimal network configuration was determined to be 2–14–5, based on variations in the number of neurons. The optimal model achieved a correlation coefficient (R) of 0.99601, and it was thoroughly evaluated using metrics such as R^2, MAPE, MSE, and RMSE. The result strongly supports earlier research [103], [104] indicating that the model accurately predicted performance and emission characteristics.

3.6. Bi-fuels

Sun et al. [24] and Javed et al. [76], [105] conducted a thorough analysis of the predictive performance of two feed-forward ANN models, each featuring two unknown sheet. Models predict the operational efficiency and exhaust outputs of a hydrogen dual-fuel diesel engine using Jatropha methyl eseter blends, focusing on inputs like fuel blend and hydrogen flow, and outputs such as efficiency and emissions. All parameters were properly normalized within the range of 0.1 to 0.9. The study systematically evaluated five combinations of activation functions: tansig-tansig, logsig-tansig, purelin-tansig, logsig-logsig, and tansig-logsig. The model underwent training over centennial cycle, with a least gradient threshold set to 10-7 and a maximum of 10,000 epochs. Data partitioning followed a 70% training, 15% validation, and 15% testing split. The number of neurons in the unknown sheet was adjusted strategically. Performance was assessed using evaluation metrics such as the R, MSE, and mean absolute percentage error (MAPE). The best-performing configuration employed dual-layer configuration with 16 neurons, producing the most favorable results. Moreover, in another notable study, [86], [106]. They used a neural network for predicting engine performance metrics for various dual-fuel blends, including 100% diesel, 100% biodiesel, and ethanol-biodiesel blends, tested at across varying engine speeds. The feature set consisted of 96 metrics, normalized between 0% and 100%, with 75% used for training and 25% for testing. While the authors noted four output layers, they clearly intended to reference four output neurons. The optimal ANN configuration was 2-28-4, using MSE as the cost function, the tansig activation function, and a learning rate of 0.3. The model achieved high correlation coefficients (R) for power, torque, SFC, and fuel consumption, reaching 0.99977 and 0.99944, 0.99999 and 0.99989, 0.99997 and 0.99983, and 0.9952 and 0.99858 for training and testing. A t-test showed no significant difference between predicted and experimental values, further validating the model's accuracy and dependability, which also has similarities with previous research using similar fuels [20], [35], [107].

3.7. Summary

Based on the literature reviewed, we identified key findings and major issues, as shown in **Table 2**.

Table 2. Summary of the key findings and major issues discussed

Fuels	Hidden layer activation function(s) and learning algorithm	Input	Output	Performance indicators	References
Gasoline-bioethanol	Amplified Gradient Conjugation	RPM and fuel mixture proportion	Indicated pressure deviation factor	R2	[23], [33], [40], [52], [53], [64]
Gasoline-ethanol	Logsig trainlm	RPM and fuel mixture proportion	Braking output, RPM, SFC, ηth, airflow efficiency, emission metrics	R and RMSE	[54], [55]
Butanol-diesel	Amplified gradient conjugation	RPM and fuel mixture proportion	Indicated pressure deviation factor	MAPE, R2	[56]–[58], [66]
	Tansig, trainlm	Intake temperature and RPM	Indicated pressure deviation factor, low-oxygen exhaust compound, nitrogen-based emissions, and ηth	R2, RMSE and mean error coefficient	[59]–[61]
Petro-fuel-methanol	Tansig-tansig trainscg	RPM, fuel mixture	Spin force, engine brake, low-oxygen exhaust compound, CO_2, fuel particulate emissions, and nitrogen-based emissions	R	[55], [62], [63]
Gasoline-methanol and ethanol	Tansig and trainlm	RPM, fuel mixture	Engine performance metrics and fuel consumption prediction	R, R2, RMSE, error coefficient, and the heading accuracy	[57], [65]
Crude glycerol-diesel oil	Tansig and trainlm	Hybrid fuel mixture, engine workload	Energy Conversion Rate (ECR), emission heat level and energy efficiency predictor, emission metrics	RMSE, R2, MAPE, MSRE, and U2 error measure	[70]–[72]
Frying oil biodiesel and diesel hybrid fuel	Logsig Trainlm	RPM and mixed combustion fuel	Spin force, fuel efficiency, emission metrics	R	[73]–[75]

Fuels	Hidden layer activation function(s) and learning algorithm	Input	Output	Performance indicators	References
Jatropha ethyl ester- diesel	Logsig Trainlm	Engine strain percentage, fuel variant, engine compression index (ECI) and injector activation point	ECR, energy efficiency predictor, Emission heat level, emission metrics	R, MRE	[76]
FAMEs oil (Jatropha, Karanja, Mahua, and Neem) diesel blends	Logsig trainlm	ECI, injector activation point, engine strain and fuel variant	ECR, Energy efficiency predictor, Emission heat level, emission metrics, and soot	R, MSE and MAPE	[77]–[79]
Citronella oil and coconut oil ethyl esters	Logsig trainlm, trainscg	Engine strain percentage, fuel variant, engine compression index and injector activation point	ECR, Energy efficiency predictor, Emission heat level, emission metrics, and soot	RMS, R2 and mean error coefficient	[75], [80]–[82]
Crude coconut, palm, and pure diesel	tansig trainlm	Engine strain, fuel variant, and protective layer	Fuel efficiency predictor, ECR, emission metrics	R, mean proportional deviation	[74], [83]
Soy biodiesel, a palm-diesel blend, and pure diesel	tansig trainlm	Revolutions rate, spin force, combustion feed rate and fuel variant	Power output , emission metrics	R	[84], [85]
Karanja and algae Oil (B20, B40, B80, and B95)	Tansig, Trainlm	Power output, sustainable fuel mix	Fuel efficiency predictor, ECR, emission and soot metrics	R	[62], [86], [87]
Hydrogen-based fuel	Tansig and logsig	Engine strain and the hydrogen supply flow	ECR, fuel efficiency predictor, emission and soot metrics	R2, RMSE, MAPE, and KGE	[88], [89]
Hydrogen with a mixture of prosopis juliflora	tansig trainlm	RPM, throttle valve angle, airflow mass rate, air intake system pressure, engine output metrics, fuel-airtight ratio, and exhaust thermal output	Power system behavior and emission trends	Average error (value and %), standard deviation (STD), RMSE (value and %).	[90]
Hydrogen-pure diesel	Logsig-tansig trainlm	Engine Strain, Hydrogen supply flow	Soot, emission index, UHC, CO_2, energy efficiency predictor, and ECR	R, MRE, MSRE, RMSE, MAPE, R2	[91]–[95]
CNG-diesel	Logsig trainlm	Revolutions rate and CNG-Diesel hybrid fuel	Shaft output power, torque, fuel efficiency predictor, ECR, Power system behavior and emission trends	R, MRE and RMSE	[96]–[98]
CNG-diesel dual-fuel system	Logsig-logsig Trainlm	Engine strain, combustion feed rate and compressed gas fuel	Fuel efficiency predictor, ECR, nitrogen-based emissions, PM and fuel particulate emissions	R, R2, MSE, RMSE and MAPE	[99], [100]
LPG	Logsig trainlm	Revolutions rate	Engine output metrics and pollution characteristics,	R, MRE, RMSE	[101], [102]

Fuels	Hidden layer activation function(s) and learning algorithm	Input	Output	Performance indicators	References
LPG	Logsig trainlm	Engine strain, LPG consumption rate	Fuel efficiency predictor, nitrogen-based emissions, fuel particulate emissions, smoke and low-oxygen exhaust compound	R, R2, MAPE, MSE and RMSE	[103], [104]
Hydrogen-Jatropha methyl eseter blends	Logsig-logsig trainlm	Engine strain, biodiesel blend, hydrogen consumption rate	ECR, fuel efficiency predictor, low-oxygen exhaust compound, O_2, CO_2, nitrogen-based emissions, fuel particulate emissions and EGT	R, MSE and MAPE	[24], [105]
Diesel-biodiesel, and Diesel-ethanol-biodiesel	Tansig	Mixed combustion fuel, RPM	Power output, spin force, fuel efficiency predictor and fuel consumption	R	[86], [106]
Diesel-ethanol-biodiesel	Logsig trainlm	Revolutions rate, ignition quality index, effective calorific value, and volumetric mass density	Spin force, low-oxygen exhaust compound and nitrogen-based emissions	R2	[20], [35], [107]

4. Conclusion

This study highlights the essential contribution of ANN in enhancing the efficiency of alternative fuels while minimizing their environmental impact. Research indicates that ANN is highly effective in modeling, optimizing, and predicting various alternative fuels' physicochemical properties and combustion processes, including ethanol, methanol, butanol, CNG, LPG, hydrogen, and biodiesel. The utilization of ANN for forecasting combustion parameters can lead to fuel efficiency improvements of 15-25%, alongside a reduction in exhaust emissions by 20-30%. ANN models frequently demonstrate a high coefficient of determination (R^2) exceeding 0.99, underscoring their superior accuracy to traditional mathematical models. Moreover, correlation coefficients (R) often approach 0.98, indicating a robust relationship between the predicted parameters and observed outcomes. Furthermore, ANN has been shown to decrease the variability in emission predictions inherent in traditional models by as much as 10%, thereby enhancing the overall quality of the model. Through the application of ANN, combustion parameters can be optimized, resulting in enhanced fuel efficiency, reduced exhaust emissions, and improved engine performance. Multiple studies have reported that optimization via ANN can lead to a 10-15% increase in combustion efficiency and a 5-10% enhancement in engine performance under specific conditions.

Although the use of ANN goes beyond forecasting engine performance and emissions, it is important to recognize the difficulties involved in collecting high-quality data and creating efficient algorithms. Moreover, the percentage error typically ranges between 2-8% across various studies, reflecting minimal relative error in ANN predictions. Direction accuracy (DA) has been observed to exceed 90% in several instances, further affirming the precision of the ANN model in predicting the direction of changes in relevant parameters. The potential of ANN to facilitate sustainable energy development is substantial. Numerous studies have evidenced that deploying ANN in combustion systems can considerably reduce CO_2 emissions by 25-30%. As advancements in computing technology continue, ANNs are anticipated to remain a crucial resource in the research and development of alternative fuels, contributing to enhanced energy efficiency and a significant reduction in environmental impact. Looking forward, it is expected that R^2 values will approach 1.0 in future applications as both data quality and optimization algorithms improve.

5. Future recommendation

A detailed exploration of the application of artificial neural networks (ANNs) in internal combustion engines would significantly strengthen these methodologies within the field, particularly given their exceptional ability to generate highly accurate models. Thus, it is advisable to pursue further research on this subject. A thorough investigation that employs both modeling approaches, focusing on variables such as engine injection timing, the effects of compression ratios, air-fuel ratios, and various combustion chamber geometries, would provide critical insights into the impact of alternative fuels on spark ignition and compression ignition engines, especially regarding combustion behavior, performance, and exhaust emissions.

Moreover, evaluating a diverse array of machine learning algorithms, including reinforcement learning, k-nearest neighbors, bootstrap aggregating, temporal difference learning, Q-learning, genetic algorithms, and support vector machines, could yield valuable perspectives on their effectiveness in predicting engine performance and emissions. Additionally, conducting studies on various internal combustion engine designs that utilize blended fuels in spark and compression ignition engines would enhance our understanding of their combustion characteristics, performance metrics, and emission profiles. Finally, further research is warranted to assess the durability of these systems under varying temperature conditions.

Acknowledgments

We proudly acknowledge the vital support from the Ministry of Education, Culture, Research, and Technology of Indonesia for their financial assistance in this research. We also celebrate the unwavering dedication of the Fuel Engineering and Combustion Technology Laboratory at Jayapura University of Science and Technology in bringing this work to fruition.

Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

Funding – Indonesia's Ministry of Education, Culture, Research, and Technology funded this research under grant number 02/LPPM-USTJ/N/VI/2024.

Availability of data and materials - All data is available from the authors.

Competing interests - The authors declare no competing interest.

Additional information – No additional information from the authors.

References

[1] M. Larsen and J. P. Tilsted, "The future of fossil fuels, chemicals, and feedstocks: Outlining a research agenda on the role of China in the global petrochemical industry," *Energy Research & Social Science*, vol. 118, p. 103750, Dec. 2024, doi: 10.1016/J.ERSS.2024.103750.

[2] S. M. Gomes *et al.*, "Nexus among climate change, food systems, and human health: An interdisciplinary research framework in the Global South," *Environmental Science & Policy*, vol. 161, p. 103885, Nov. 2024, doi: 10.1016/J.ENVSCI.2024.103885.

[3] F. Lien, Å. Lappegard, and M. Kollberg, "User evaluation of a national web portal for climate change adaptation – A qualitative case sstudy of the Knowledge Bank," *Climate Services*, vol. 30, no. September 2021, 2023, doi: 10.1016/j.cliser.2023.100367.

[4] S. Moradian, S. Gharbia, M. Majidi Nezhad, and A. I. Olbert, "Enhancing the accuracy of wind power projections under climate change using geospatial machine learning models," *Energy Reports*, vol. 12, pp. 3353–3363, Dec. 2024, doi: 10.1016/J.EGYR.2024.09.007.

[5] H. Karunathilake and S. Witharana, "Fossil Fuels and Global Energy Economics," *Encyclopedia of Renewable Energy, Sustainability and the Environment*, pp. 107–120, Jan. 2024, doi: 10.1016/B978-0-323-93940-9.00050-5.

[6] S. D. Shelare *et al.*, "Biofuels for a sustainable future: Examining the role of nano-additives, economics, policy, internet of things, artificial intelligence and machine learning technology

in biodiesel production," *Energy*, vol. 282, p. 128874, Nov. 2023, doi: 10.1016/J.ENERGY.2023.128874.

[7] M. A. Aktar, M. M. Alam, and A. Q. Al-Amin, "Global economic crisis, energy use, CO2 emissions, and policy roadmap amid COVID-19," *Sustainable Production and Consumption*, vol. 26, pp. 770–781, 2021, doi: 10.1016/j.spc.2020.12.029.

[8] H. Y. Nanlohy, H. Riupassa, and M. Setiyo, "Characterizing of Nano Activated Bio-Carbon of Sago Waste as a Homogeneous Combustion Catalyst," *Automotive Experiences*, vol. 7, no. 1, pp. 77–85, Apr. 2024, doi: 10.31603/AE.10619.

[9] B. P. Sandaka and J. Kumar, "Alternative vehicular fuels for environmental decarbonization: A critical review of challenges in using electricity, hydrogen, and biofuels as a sustainable vehicular fuel," *Chemical Engineering Journal Advances*, vol. 14, p. 100442, May 2023, doi: 10.1016/J.CEJA.2022.100442.

[10] H. Riupassa, S. Suyatno, and H. Y. Nanlohy, "Identifying the Effect of Aromatic Compounds on the Combustion Characteristics of Crude Coconut Oil Droplet," *Eastern-European Journal of Enterprise Technologies*, vol. 2, no. 6–122, pp. 6–14, 2023, doi: 10.15587/1729-4061.2023.272289.

[11] H. Y. Nanlohy, "Performance and Emissions Analysis of BE85-Gasoline Blends on Spark Ignition Engine," *Automotive Experiences*, vol. 5, no. 1, pp. 40–48, 2022, doi: https://doi.org/10316/ae.6116.

[12] J. Milano *et al.*, "A Comprehensive exploration of jatropha curcas biodiesel production as a viable alternative feedstock in the fuel industry – Performance evaluation and feasibility analysis," *Mechanical Engineering for Society and Industry*, vol. 4, no. 1, pp. 17–37, Apr. 2024, doi: 10.31603/mesi.10610.

[13] S. Munahar, B. C. Purnomo, and H. Köten, "Fuel Control Systems for Planetary Transmission Vehicles: A Contribution to the LPG-fueled Vehicles Community," *Mechanical Engineering for Society and Industry*, vol. 1, no. 1, pp. 14–21, 2021, doi: 10.31603/mesi.5263.

[14] L. M. Olalekan, O. Olatunde, F. I. Oluwafemi, and A. A. Olamide, "Mathematical modeling and cost comparison for electricity generation from petrol and liquified petroleum gas (LPG)," *Mechanical Engineering for Society and Industry*, vol. 2, no. 2, pp. 57–63, 2022, doi: 10.31603/mesi.6697.

[15] H. Y. Nanlohy, I. N. G. Wardana, M. Yamaguchi, and T. Ueda, "The role of rhodium sulfate on the bond angles of triglyceride molecules and their effect on the combustion characteristics of crude jatropha oil droplets," *Fuel*, vol. 279, p. 118373, 2020, doi: 10.1016/j.fuel.2020.118373.

[16] H. Y. Nanlohy, I. N. G. Wardana, N. Hamidi, L. Yuliati, and T. Ueda, "The effect of Rh^{3+} catalyst on the combustion characteristics of crude vegetable oil droplets," *Fuel*, vol. 220, 2018, doi: 10.1016/j.fuel.2018.02.001.

[17] M. Aghbashlo *et al.*, "Machine learning technology in biodiesel research: A review," *Progress in Energy and Combustion Science*, vol. 85, p. 100904, 2021, doi: 10.1016/j.pecs.2021.100904.

[18] H. Y. Nanlohy, S. Sarikoc, and M. Setiyo, "Dynamical Behavior of Droplet Diffusion Flame of Blended Castor Oil with Metal Based Liquid Catalyst," *Automotive Experiences*, vol. 7, no. 2, pp. 310–320, 2024.

[19] Y. Chen *et al.*, "The combustion process of methyl ester-biodiesel in the presence of different nanoparticles: A molecular dynamics approach," *Journal of Molecular Liquids*, vol. 373, p. 121232, Mar. 2023, doi: 10.1016/J.MOLLIQ.2023.121232.

[20] K. R. Kirankumar, G. N. Kumar, N. Kamath, and K. V. Gangadharan, "Experimental investigation and optimization of performance, emission, and vibro-acoustic parameters of SI engine fueled with n-propanol and gasoline blends using ANN-GA coupled with NSGA3-modified TOPSIS hybrid approach," *Energy*, vol. 306, p. 132521, Oct. 2024, doi: 10.1016/J.ENERGY.2024.132521.

[21] J. Baehr *et al.*, "Predicting product life cycle environmental impacts with machine learning: Uncertainties and implications for future reporting requirements," *Sustainable Production and Consumption*, vol. 52, pp. 511–526, Dec. 2024, doi: 10.1016/J.SPC.2024.11.005.

[22] K. Kishore Khatri, M. Singh, and N. Khatri, "An artificial neural network model for the

prediction of performance and emission parameters of a CI engine-operated micro-tri-generation system fueled with diesel, Karanja oil, and Karanja biodiesel," *Fuel*, vol. 334, Feb. 2023, doi: 10.1016/J.FUEL.2022.126549.

[23] S. Marianingsih, F. Mar'i, and H. Y. Nanlohy, "Artificial Neural Network-Based Modeling of Performance Spark Ignition Engine Fuelled with Bioethanol and Gasoline," *Journal of Mechanical Engineering Science and Technology (JMEST)*, vol. 7, no. 2, p. 190, 2023, doi: 10.17977/um016v7i22023p190.

[24] P. Sun *et al.*, "Artificial neural network models for forecasting the combustion and emission characteristics of ethanol/gasoline DFSI engines with combined injection strategy," *Case Studies in Thermal Engineering*, vol. 54, p. 104007, Feb. 2024, doi: 10.1016/J.CSITE.2024.104007.

[25] A. I. Petrov and A. V Pistsov, "Training and Applying Artificial Neural Networks in Traffic Light Control: Improving the Management and Safety of Road Traffic in Tyumen (Russia)," *Automotive Experiences*, vol. 6, no. 3, pp. 528–550, 2023, doi: 10.31603/ae.10025.

[26] S. Patnaik, N. Khatri, and E. R. Rene, "Artificial neural networks-based performance and emission characteristics prediction of compression ignition engines powered by blends of biodiesel derived from waste cooking oil," *Fuel*, vol. 370, p. 131806, Aug. 2024, doi: 10.1016/J.FUEL.2024.131806.

[27] K. Salari, P. Zarafshan, M. Khashehchi, E. Pipelzadeh, and G. Chegini, "Modeling and predicting of water production by capacitive deionization method using artificial neural networks," *Desalination*, vol. 540, Oct. 2022, doi: 10.1016/j.desal.2022.115992.

[28] S. M. N. Rahaju, A. L. Hananto, P. A. Paristiawan, A. T. Mohammed, A. C. Opia, and M. Idris, "Comparison of Various Prediction Model for Biodiesel Cetane Number using Cascade-Forward Neural Network," *Automotive Experiences*, vol. 6, no. 1, pp. 4–13, Jan. 2023, doi: 10.31603/ae.7050.

[29] A. Kolakoti, B. Prasadarao, K. Satyanarayana, M. Setiyo, H. Köten, and M. Raghu, "Elemental, Thermal and Physicochemical Investigation of Novel Biodiesel from Wodyetia Bifurcata and Its Properties Optimization using Artificial Neural Network (ANN)," *Automotive Experiences*, vol. 5, no. 1, pp. 3–15, 2022, doi: 10.31603/ae.6171.

[30] A. Kolakoti, M. Setiyo, and M. L. Rochman, "A Green Heterogeneous Catalyst Production and Characterization for Biodiesel Production using RSM and ANN Approach," *International Journal of Renewable Energy Development*, vol. 11, no. 3, pp. 703–712, 2022, doi: 10.14710/ijred.2022.43627.

[31] R. Karami, M. G. Rasul, M. M. K. Khan, and M. Mahdi Salahi, "Experimental and computational analysis of combustion characteristics of a diesel engine fueled with diesel-tomato seed oil biodiesel blends," *Fuel*, vol. 285, p. 119243, Feb. 2021, doi: 10.1016/J.FUEL.2020.119243.

[32] P. Sun, J. Zhang, W. Dong, D. Li, and X. Yu, "Prediction of oxygen-enriched combustion and emission performance on a spark ignition engine using artificial neural networks," *Applied Energy*, vol. 348, p. 121466, Oct. 2023, doi: 10.1016/J.APENERGY.2023.121466.

[33] D. J. Godwin, E. G. Varuvel, and M. L. J. Martin, "Prediction of combustion, performance, and emission parameters of ethanol powered spark ignition engine using ensemble Least Squares boosting machine learning algorithms," *Journal of Cleaner Production*, vol. 421, Oct. 2023, doi: 10.1016/j.jclepro.2023.138401.

[34] L. L. G M, C. Das M, R. Jayabal, M. S, S. D, and M. N, "Experimental evaluation and neural network modelling of reactivity-controlled compression ignition engine using cashew nut shell oil biodiesel-alumina nanoparticle blend and gasoline injection," *Energy*, vol. 282, p. 128923, Nov. 2023, doi: 10.1016/J.ENERGY.2023.128923.

[35] C. zhe Zhu *et al.*, "Artificial neural networks vs. gene expression programming for predicting emission & engine efficiency of SI operated on blends of gasoline-methanol-hydrogen fuel," *Case Studies in Thermal Engineering*, vol. 49, p. 103109, Sep. 2023, doi: 10.1016/J.CSITE.2023.103109.

[36] A. B. V. Barboza, S. Mohan, and P. Dinesha, "On reducing the emissions of CO, HC, and NOx from gasoline blended with hydrogen peroxide and ethanol: Optimization study aided with ANN-PSO," *Environmental Pollution*, vol. 310, p. 119866, Oct. 2022, doi: 10.1016/J.ENVPOL.2022.119866.

[37] K. Szramowiat-Sala *et al.*, "AI-based data mining approach to control the environmental impact of conventional energy technologies," *Journal of Cleaner Production*, vol. 472, p. 143473, Sep. 2024, doi: 10.1016/J.JCLEPRO.2024.143473.

[38] I. Cesur and F. Uysal, "Experimental investigation and artificial neural network-based modelling of thermal barrier engine performance and exhaust emissions for methanol-gasoline blends," *Energy*, vol. 291, p. 130393, Mar. 2024, doi: 10.1016/J.ENERGY.2024.130393.

[39] M. R. Atelge, "Investigation of a ternary blend of diesel/ethanol/n-butanol with binary nano additives on combustion and emission: A modeling and optimization approach with artificial neural networks," *Fuel Processing Technology*, vol. 229, p. 107155, May 2022, doi: 10.1016/J.FUPROC.2021.107155.

[40] A. Taheri-Garavand, A. Heidari-Maleni, T. Mesri-Gundoshmian, and O. D. Samuel, "Application of artificial neural networks for the prediction of performance and exhaust emissions in IC engine using biodiesel-diesel blends containing quantum dot based on carbon doped," *Energy Conversion and Management: X*, vol. 16, p. 100304, 2022, doi: https://doi.org/10.1016/j.ecmx.2022.100304.

[41] S. R. Ariyanto, S. Suprayitno, and R. Wulandari, "Design of Metallic Catalytic Converter using Pareto Optimization to Improve Engine Performance and Exhaust Emissions," *Automotive Experiences*, vol. 6, no. 1, pp. 200–2015, Apr. 2023, doi: 10.31603/ae.7977.

[42] M. I. Shahid, A. Rao, M. Farhan, Y. Liu, and F. Ma, "Optimizing heat transfer predictions in HCNG engines: A novel model validation and comparative study via quasi-dimensional combustion modeling and artificial neural networks," *International Journal of Hydrogen Energy*, vol. 83, pp. 1263–1281, Sep. 2024, doi: 10.1016/J.IJHYDENE.2024.08.124.

[43] M. Zihao *et al.*, "Multi-Thermal Recovery Layout for a Sustainable Power and Cooling Production by Biomass-based Multi-generation System: Techno-Economic-Environmental Analysis and ANN-GA Optimization," *Case Studies in Thermal Engineering*, p. 105589, Nov. 2024, doi: 10.1016/J.CSITE.2024.105589.

[44] S. Gürgen, B. Ünver, and İ. Altın, "Prediction of cyclic variability in a diesel engine fueled with n-butanol and diesel fuel blends using artificial neural network," *Renewable Energy*, vol. 117, pp. 538–544, Mar. 2018, doi: 10.1016/J.RENENE.2017.10.101.

[45] M. Tekin and S. Saridemir, "Prediction of engine performance and exhaust emissions with different proportions of ethanol–gasoline blends using artificial neural networks," *International Journal of Ambient Energy*, vol. 40, no. 5, pp. 470–476, Jul. 2019, doi: 10.1080/01430750.2017.1410225.

[46] S. Dey, N. M. Reang, A. Majumder, M. Deb, and P. K. Das, "A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend," *Energy*, vol. 202, Jul. 2020, doi: 10.1016/j.energy.2020.117813.

[47] R. Yang, T. Xie, and Z. Liu, "The Application of Machine Learning Methods to Predict the Power Output of Internal Combustion Engines," *Energies*, vol. 15, no. 9, May 2022, doi: 10.3390/EN15093242.

[48] M. Farhan, T. Chen, A. Rao, M. I. Shahid, Y. Liu, and F. Ma, "Comparative knock analysis of HCNG fueled spark ignition engine using different heat transfer models and prediction of knock intensity by artificial neural network fitting tool," *Energy*, vol. 304, p. 132135, Sep. 2024, doi: 10.1016/J.ENERGY.2024.132135.

[49] S. Uslu and M. B. Celik, "Performance and Exhaust Emission Prediction of a SI Engine Fueled with I-amyl Alcohol-Gasoline Blends: An ANN Coupled RSM Based Optimization," *Fuel*, vol. 265, p. 116922, Apr. 2020, doi: 10.1016/J.FUEL.2019.116922.

[50] U. Rajak, Ü. Ağbulut, A. Dasore, and T. N. Verma, "Artificial intelligence based-prediction of energy efficiency and tailpipe emissions of soybean methyl ester fuelled CI engine under variable compression ratios," *Energy*, vol. 294, p. 130861, May 2024, doi: 10.1016/J.ENERGY.2024.130861.

[51] M. Setiyo, D. Yuvenda, and O. D. Samuel, "The Concise Latest Report on the Advantages and Disadvantages of Pure Biodiesel (B100) on Engine Performance: Literature Review and Bibliometric Analysis," *Indonesian Journal of Science and Technology*, vol. 6, no. 3, pp. 469–490, 2021, doi: 10.17509/ijost.v6i3.38430.

[52] O. Y. Ahmed *et al.*, "Model Predictive Control of Combustion Phasing in Compression

Ignition Engines by Coordinating Fuel Injection Timing and Ignition Assist," *IFAC-PapersOnLine*, vol. 55, no. 24, pp. 90–96, Jan. 2022, doi: 10.1016/J.IFACOL.2022.10.267.

[53] D. J. Godwin, E. G. Varuvel, M. L. Jesu Martin, A. Jasmine R, and F. Josephin JS, "A Comparative Analysis of Advanced Machine Learning Models for the Prediction of Combustion, Emission and Performance Characteristics Using Endoscopic Combustion Flame Image of a Pine Oil–Gasoline Fuelled Spark Ignition Engine," *Journal of Cleaner Production*, p. 144284, Nov. 2024, doi: 10.1016/J.JCLEPRO.2024.144284.

[54] D. Y. Dhande, C. S. Choudhari, D. P. Gaikwad, and K. B. Dahe, "Development of artificial neural network to predict the performance of spark ignition engine fuelled with waste pomegranate ethanol blends," *Information Processing in Agriculture*, vol. 10, no. 4, pp. 459–474, Dec. 2023, doi: 10.1016/J.INPA.2022.05.001.

[55] R. Bathala, H. G, S. Rajkumar, D. A. S, and T. Jeyaseelan, "Experimental investigation, ANN modeling, and TOPSIS optimization of gasoline-alcohol blends for minimizing tailpipe emissions of a motorcycle," *Energy*, vol. 293, p. 130698, Apr. 2024, doi: 10.1016/J.ENERGY.2024.130698.

[56] Y. Zhou, F. Xie, B. Zhang, P. Sun, X. Zhang, and X. Meng, "Effects of alcohol fuels on SACI engine and analyze of prediction of SACI engine performance by artificial neural networks," *Case Studies in Thermal Engineering*, vol. 61, p. 105040, Sep. 2024, doi: 10.1016/J.CSITE.2024.105040.

[57] G. Udaybhanu and V. Mahendra Reddy, "A hybrid GA-ANN and correlation approach to developing a laminar burning velocity prediction model for isooctane/blends-air mixtures," *Fuel*, vol. 360, p. 130594, Mar. 2024, doi: 10.1016/J.FUEL.2023.130594.

[58] M. Göktaş, M. Kemal Balki, C. Sayin, and M. Canakci, "An evaluation of the use of alcohol fuels in SI engines in terms of performance, emission and combustion characteristics: A review," *Fuel*, vol. 286, no. July 2020, 2021, doi: 10.1016/j.fuel.2020.119425.

[59] V. R. Duddu, S. S. Pulugurtha, A. S. Mane, and C. Godfrey, "Back-propagation neural network model to predict visibility at a road link-level," *Transportation Research Interdisciplinary Perspectives*, vol. 8, no. October, p. 100250, 2020, doi: 10.1016/j.trip.2020.100250.

[60] H. Tarigonda, B. Anjaneyulu, R. Raghurami Reddy, and K. L. Narasimhamu, "Optimization of performance and emission characteristics of a diesel engine in dual-fuel mode with LPG using adaptive-neuro fuzzy inference system model," *Materials Today: Proceedings*, Mar. 2023, doi: 10.1016/J.MATPR.2023.02.290.

[61] N. Chacko and T. Jeyaseelan, "Comparative evaluation of graphene oxide and graphene nanoplatelets as fuel additives on the combustion and emission characteristics of a diesel engine fuelled with diesel and biodiesel blend," *Fuel Processing Technology*, vol. 204, Jul. 2020, doi: 10.1016/j.fuproc.2020.106406.

[62] P. Sujin, A. J. Kings, L. R. M. Miriam, and J. B. Marshel, "Optimized biodiesel production from mixed non-edible oils using advanced computational techniques and a novel bifunctional liquified catalyst: Compatibility assessment in IC engines," *Biomass and Bioenergy*, vol. 190, p. 107412, Nov. 2024, doi: 10.1016/J.BIOMBIOE.2024.107412.

[63] D. Jesu Godwin *et al.*, "Effect of hydroxyl (OH) group position in alcohol on performance, emission and combustion characteristics of SI engine," *Energy Conversion and Management*, vol. 189, no. April, pp. 195–201, 2019, doi: 10.1016/j.enconman.2019.03.063.

[64] S. Cheng, S. Scott Goldsborough, C. Saggese, S. W. Wagnon, and W. J. Pitz, "New insights into fuel blending effects: Intermolecular chemical kinetic interactions affecting autoignition times and intermediate-temperature heat release," *Combustion and Flame*, vol. 233, p. 111559, Nov. 2021, doi: 10.1016/J.COMBUSTFLAME.2021.111559.

[65] H. A. AlNazr, N. Ahmad, U. Ahmed, B. Mohan, and A. G. Abdul Jameel, "Predicting physical properties of oxygenated gasoline and diesel range fuels using machine learning," *Alexandria Engineering Journal*, vol. 76, pp. 193–219, Aug. 2023, doi: 10.1016/J.AEJ.2023.06.037.

[66] B. Nanda Behera and T. Kumar Hotta, "Influence of copper oxide nano-particles on the performance, emission, and combustion measures of a VCR engine using palm biodiesel blended with N-butanol: A combined experimental and ANN-GA-based study," *Fuel*, vol. 381, p. 133504, Feb. 2025, doi: 10.1016/J.FUEL.2024.133504.

[67] A. Kumar Prajapati *et al.*, "Process intensification in biodiesel production using unconventional reactors," *Fuel*, vol. 380, p. 133263, Jan. 2025, doi: 10.1016/J.FUEL.2024.133263.

[68] M. Tabatabaei *et al.*, "Reactor technologies for biodiesel production and processing: A review," *Progress in Energy and Combustion Science*, vol. 74, pp. 239–303, Sep. 2019, doi: 10.1016/J.PECS.2019.06.001.

[69] H. K. Ismaeel *et al.*, "Strategies for biodiesel production with the role of reactor technologies: A comprehensive review," *Chemical Engineering and Processing - Process Intensification*, vol. 200, p. 109767, Jun. 2024, doi: 10.1016/J.CEP.2024.109767.

[70] A. K. Pradhan, H. Goyal, P. Patel, and P. Mondal, "Bio-hydrogen production from crude glycerol: Optimisation through response surface methodology and artificial neural network approach," *Biomass and Bioenergy*, vol. 185, p. 107243, Jun. 2024, doi: 10.1016/J.BIOMBIOE.2024.107243.

[71] S. V. Khandal *et al.*, "Hydrogen and dual fuel mode performing in engine with different combustion chamber shapes: Modelling and analysis using RSM-ANN technique," *International Journal of Hydrogen Energy*, vol. 52, pp. 973–1005, Jan. 2024, doi: 10.1016/J.IJHYDENE.2022.09.193.

[72] B. Ashok *et al.*, "Multi-functional fuel additive as a combustion catalyst for diesel and biodiesel in CI engine characteristics," *Fuel*, vol. 278, no. May, p. 118250, 2020, doi: 10.1016/j.fuel.2020.118250.

[73] M. El-Adawy, "Effects of diesel-biodiesel fuel blends doped with zinc oxide nanoparticles on performance and combustion attributes of a diesel engine," *Alexandria Engineering Journal*, vol. 80, no. March, pp. 269–281, 2023, doi: 10.1016/j.aej.2023.08.060.

[74] W. Bajwa *et al.*, "Optimization of biodiesel yield from waste cooking oil and sesame oil using RSM and ANN techniques," *Heliyon*, vol. 10, no. 15, p. e34804, Aug. 2024, doi: 10.1016/J.HELIYON.2024.E34804.

[75] K. Ramalingam *et al.*, "Substitution of diesel fuel in conventional compression ignition engine with waste biomass-based fuel and its validation using artificial neural networks," *Process Safety and Environmental Protection*, vol. 177, pp. 1234–1248, Sep. 2023, doi: 10.1016/J.PSEP.2023.07.085.

[76] S. Javed, Y. V. V. Satyanarayana Murthy, R. U. Baig, and D. Prasada Rao, "Development of ANN model for prediction of performance and emission characteristics of hydrogen dual fueled diesel engine with Jatropha Methyl Ester biodiesel blends," *Journal of Natural Gas Science and Engineering*, vol. 26, pp. 549–557, Sep. 2015, doi: 10.1016/J.JNGSE.2015.06.041.

[77] S. Sayyed, R. K. Das, and K. Kulkarni, "Performance assessment of multiple biodiesel blended diesel engine and NOx modeling using ANN," *Case Studies in Thermal Engineering*, vol. 28, Dec. 2021, doi: 10.1016/j.csite.2021.101509.

[78] S. Uslu, "Optimization of diesel engine operating parameters fueled with palm oil-diesel blend: Comparative evaluation between response surface methodology (RSM) and artificial neural network (ANN)," *Fuel*, vol. 276, p. 117990, Sep. 2020, doi: 10.1016/J.FUEL.2020.117990.

[79] F. Fangfang, A. Alagumalai, and O. Mahian, "Sustainable biodiesel production from waste cooking oil: ANN modeling and environmental factor assessment," *Sustainable Energy Technologies and Assessments*, vol. 46, p. 101265, Aug. 2021, doi: 10.1016/J.SETA.2021.101265.

[80] I. Veza *et al.*, "Review of artificial neural networks for gasoline, diesel and homogeneous charge compression ignition engine," *Alexandria Engineering Journal*, vol. 61, no. 11, pp. 8363–8391, 2022, doi: 10.1016/j.aej.2022.01.072.

[81] Y. Singh, A. Sharma, G. Kumar Singh, A. Singla, and N. Kumar Singh, "Optimization of performance and emission parameters of direct injection diesel engine fuelled with pongamia methyl esters-response surface methodology approach," *Industrial Crops and Products*, vol. 126, pp. 218–226, Dec. 2018, doi: 10.1016/J.INDCROP.2018.10.035.

[82] C. N. Ude *et al.*, "Sustainable Chemistry for the Environment Optimization of dual transesterification of jatropha seed oil to biolubricant using hybridized response surface methodology (RSM) and adaptive neuro fuzzy inference system (ANFIS) -genetic algorithm

(GA)," *Sustainable Chemistry for the Environment*, vol. 4, no. April, p. 100050, 2023, doi: 10.1016/j.scenv.2023.100050.

[83] P. Sharma, "Data-driven predictive model development for efficiency and emission characteristics of a diesel engine fueled with biodiesel/diesel blends," *Artificial Intelligence for Renewable Energy systems*, pp. 329–352, Jan. 2022, doi: 10.1016/B978-0-323-90396-7.00005-5.

[84] J. Thangaraja, L. Zigan, and S. Rajkumar, "A machine learning framework for evaluating the biodiesel properties for accurate modeling of spray and combustion processes," *Fuel*, vol. 334, p. 126573, Feb. 2023, doi: 10.1016/J.FUEL.2022.126573.

[85] B. Işcan, "ANN modeling for justification of thermodynamic analysis of experimental applications on combustion parameters of a diesel engine using diesel and safflower biodiesel fuels," *Fuel*, vol. 279, p. 118391, Nov. 2020, doi: 10.1016/J.FUEL.2020.118391.

[86] S. Chaki and T. K. Biswas, "An ANN-entropy-FA model for prediction and optimization of biodiesel-based engine performance," *Applied Soft Computing*, vol. 133, p. 109929, Jan. 2023, doi: 10.1016/J.ASOC.2022.109929.

[87] A. A. Al-jabiri *et al.*, "Applied AMT machine learning and multi-objective optimization for enhanced performance and reduced environmental impact of sunflower oil biodiesel in compression ignition engine," *International Journal of Thermofluids*, vol. 24, p. 100838, Nov. 2024, doi: 10.1016/J.IJFT.2024.100838.

[88] K. J. Reddy, G. A. Prasad Rao, R. M. Reddy, and Ü. Aĝbulut, "Artificial intelligence-based forecasting of dual-fuel mode CI engine behaviors powered with the hydrogen-diesel blends," *International Journal of Hydrogen Energy*, vol. 87, pp. 1074–1086, Oct. 2024, doi: 10.1016/J.IJHYDENE.2024.08.507.

[89] M.-H. Tayarani-N. and A. Paykani, "An ensemble learning algorithm for optimization of spark ignition engine performance fuelled with methane/hydrogen blends," *Applied Soft Computing*, p. 112468, Nov. 2024, doi: 10.1016/J.ASOC.2024.112468.

[90] B. Musthafa and M. A. Asokan, "Numerical and experimental investigation of performance and emission characteristics of hydrogen enrichment with prosopis juliflora biodiesel in CI engine using RSM and ANN optimization," *International Journal of Hydrogen Energy*, vol. 66, pp. 326–336, May 2024, doi: 10.1016/J.IJHYDENE.2024.04.083.

[91] A. Shirneshan, B. Kanberoglu, and G. Gonca, "Experimental investigation and parametric modeling of the effect of alcohol addition on the performance and emissions characteristics of a diesel engine fueled with biodiesel-diesel-hydrogen fuel mixtures," *Fuel*, vol. 381, p. 133489, Feb. 2025, doi: 10.1016/J.FUEL.2024.133489.

[92] O. Khan, I. Alsaduni, M. Parvez, Z. Yahya, and A. K. Yadav, "Role of hydrogen-enrichment on performance and emission characteristics of a diesel engine fuelled with metal oxide nanoparticles added biodiesel/diesel blends:A combined neuro Fuzzy-Gaussian Mixture Model analysis," *International Journal of Hydrogen Energy*, vol. 93, pp. 1113–1126, Dec. 2024, doi: 10.1016/J.IJHYDENE.2024.11.032.

[93] L. K. Prajapati, J. V. Tirkey, P. Jena, and A. Giri, "Parametric performance evaluation of SI engine using producer gas-biogas-hydrogen blend as a fuel: A thermodynamic modeling and optimization approach," *International Journal of Hydrogen Energy*, vol. 72, pp. 268–287, Jun. 2024, doi: 10.1016/J.IJHYDENE.2024.05.386.

[94] Z. Liang *et al.*, "Co-optimization and prediction of high-efficiency combustion and zero-carbon emission at part load in the hydrogen direct injection engine based on VVT, split injection and ANN," *Energy*, vol. 308, p. 133038, Nov. 2024, doi: 10.1016/J.ENERGY.2024.133038.

[95] E. Ramachandran *et al.*, "Prediction of RCCI combustion fueled with CNG and algal biodiesel to sustain efficient diesel engines using machine learning techniques," *Case Studies in Thermal Engineering*, vol. 51, p. 103630, Nov. 2023, doi: 10.1016/J.CSITE.2023.103630.

[96] R. K. Mehra, H. Duan, S. Luo, A. Rao, and F. Ma, "Experimental and artificial neural network (ANN) study of hydrogen enriched compressed natural gas (HCNG) engine under various ignition timings and excess air ratios," *Applied Energy*, vol. 228, pp. 736–754, Oct. 2018, doi: 10.1016/J.APENERGY.2018.06.085.

[97] S. Mohanty and S. Paul, "A frame work for comparative wear based failure analysis of CNG and diesel operated engines," *Energy*, vol. 269, p. 126675, Apr. 2023, doi:

10.1016/J.ENERGY.2023.126675.

[98] S. K. Pathak, A. Nayyar, and V. Goel, “Optimization of EGR effects on performance and emission parameters of a dual fuel (Diesel + CNG) CI engine: An experimental investigation,” *Fuel*, vol. 291, p. 120183, May 2021, doi: 10.1016/J.FUEL.2021.120183.

[99] T. F. Yusaf, D. R. Buttsworth, K. H. Saleh, and B. F. Yousif, “CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network,” *Applied Energy*, vol. 87, no. 5, pp. 1661–1669, May 2010, doi: 10.1016/J.APENERGY.2009.10.009.

[100] S. Sahoo, V. N. S. P. Kumar, and D. K. Srivastava, “Quantitative analysis of engine parameters of a variable compression ratio CNG engine using machine learning,” *Fuel*, vol. 311, p. 122587, Mar. 2022, doi: 10.1016/J.FUEL.2021.122587.

[101] N. Kara Togun and S. Baysec, “Prediction of torque and specific fuel consumption of a gasoline engine by using artificial neural networks,” *Applied Energy*, vol. 87, no. 1, pp. 349–355, 2010, doi: 10.1016/j.apenergy.2009.08.016.

[102] A. Chakraborty, S. Roy, and R. Banerjee, “An experimental based ANN approach in mapping performance-emission characteristics of a diesel engine operating in dual-fuel mode with LPG,” *Journal of Natural Gas Science and Engineering*, vol. 28, pp. 15–30, Jan. 2016, doi: 10.1016/J.JNGSE.2015.11.024.

[103] C. J. T. Renald and P. Somasundaram, “Experimental Investigation on Attenuation of Emission with Optimized LPG Jet Induction in a Dual Fuel Diesel Engine and Prediction by ANN Model,” *Energy Procedia*, vol. 14, pp. 1427–1438, Jan. 2012, doi: 10.1016/J.EGYPRO.2011.12.1113.

[104] S. Pitchaiah, D. Juchelková, R. Sathyamurthy, and A. E. Atabani, “Prediction and performance optimisation of a DI CI engine fuelled diesel–Bael biodiesel blends with DMC additive using RSM and ANN: Energy and exergy analysis,” *Energy Conversion and Management*, vol. 292, p. 117386, Sep. 2023, doi: 10.1016/J.ENCONMAN.2023.117386.

[105] J. Syed, R. U. Baig, S. Algarni, Y. V. V. S. Murthy, M. Masood, and M. Inamurrahman, “Artificial Neural Network modeling of a hydrogen dual fueled diesel engine characteristics: An experiment approach,” *International Journal of Hydrogen Energy*, vol. 42, no. 21, pp. 14750–14774, May 2017, doi: 10.1016/J.IJHYDENE.2017.04.096.

[106] S. Seetharaman *et al.*, “Prediction, optimization, and validation of the combustion effects of diisopropyl ether-gasoline blends: A combined application of artificial neural network and response surface methodology,” *Energy*, vol. 305, p. 132185, Oct. 2024, doi: 10.1016/J.ENERGY.2024.132185.

[107] S. O. Giwa, R. T. Taziwa, and M. Sharifpur, “Dependence of composition-based approaches on hybrid biodiesel fuel properties prediction using artificial neural network and random tree algorithms,” *Renewable Energy*, vol. 218, p. 119324, Dec. 2023, doi: 10.1016/J.RENENE.2023.119324.