

Comparative Analysis of Engine Performance, Noise Emissions, and Energy Efficiency of Euro Diesel and Safflower Methyl Ester Fuels Using Artificial Neural Networks

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Abstract:

In this study, energy analysis, engine performance, and noise emission tests of Euro diesel and safflower methyl ester fuels were conducted on a diesel engine. The experiments were conducted independently for each fuel type across engine speeds ranging from 1000 to 2400 rpm, and the physicochemical properties of the fuels were characterized and evaluated through engine testing. Noise emission values were recorded from four different points around the engine at a distance of one meter and were compared with those of reference diesel fuel. According to the test results, the most suitable fuel type was determined based on engine performance, noise emission and energy analysis. In this study, modeling was performed using artificial neural networks (ANNs) based on experimentally obtained data, and the noise emission characteristics of B₁₀₀ and D¹⁰⁰ fuels were analyzed. Both raw and normalized datasets were evaluated to assess the predictive accuracy of the models. It was concluded that the predictive success was closely associated with the choice of training algorithms and transfer functions utilized. The findings highlight that selecting suitable models and algorithms tailored to the structure of the dataset plays a critical role in enhancing prediction accuracy.

Keywords: Safflower Methyl Ester, Energy Analysis, Engine Performance, Noise Emission Analysis, Artificial Neural Networks.

Highlight

- Determined the most suitable fuel type based on engine performance, noise emissions, and energy analysis.
- Conducted tests between 1000 and 2400 rpm.
- Employed an Artificial Neural Network (ANN) model for data analysis, utilizing 80% of data for training and 20% for testing.

- Compared results with reference to diesel fuel (D₁₀₀).

1. Introduction

The rapid depletion of fossil fuels is primarily driven by increasing industrialization, which escalates the demand for energy consumption [1]. Researchers are focusing on the complete replacement of petroleum-based fuels, such as biodiesel, to better reduce harmful pollutants [2]. Many countries are highly dependent on imported fossil fuels due to insufficient domestic reserves, which negatively impacts their economies [3]. Despite being regarded as an environmentally sustainable alternative to conventional diesel fuels, the utilization of pure biodiesel (B₁₀₀) in diesel engines has not yet received widespread regulatory approval. Choice of feedstock for biodiesel production is influenced by factors such as cost, feedstock availability, production techniques, and fuel stability [4]. While there are several methods for producing biodiesel, the most commonly used today is transesterification. Transesterification is an environmentally friendly process that produces liquid biofuel from oilseed crops (such as canola, sunflower, soybean and safflower) and animal fats through a reaction with a short-chain alcohol (typically methanol or ethanol) and a catalyst [5]. These characteristics can directly impact biodiesel yield and efficiency during production. In this context, both biodiesel production and the performance of the oil used are of critical importance. In particular, safflower methyl ester oil has emerged as a new and significant source for biodiesel production. The higher cetane number and lower viscosity of safflower methyl ester oil compared to conventional diesel fuel further enhance its importance. Experimental studies on safflower methyl ester have recently gained prominence.

Doğan et al. conducted numerical simulations using AVL software to compare diesel and safflower oil methyl ester (SOME) in a diesel engine across compression ratios of 12:1 to 18:1 and varying loads. SOME showed higher BSFC but lower CO and HC emissions, with increased NO_x and CO₂. Simulation results closely aligned with experimental data, particularly at higher compression ratios, confirming the model's reliability [6].

Asokan et al. investigated the impact of adding antioxidants to safflower methyl ester (B₂₀) on engine performance and emissions. The incorporation of antioxidants, namely butylated hydroxyanisole (BHA) and butylated hydroxytoluene (BHT), contributed to improved engine performance at elevated injection pressures (210 bar), with BHA in particular achieving a 5% reduction in NO_x emissions. Compared to pure diesel, B₂₀ biodiesel demonstrated lower CO and HC emissions, though there was an observed increase in NO_x emissions and smoke opacity.

The findings suggest that safflower methyl ester enriched with BHA could serve as a promising alternative fuel for diesel engines, particularly in terms of emission performance [7].

Rajendran et al. investigated the impact of injection timing on a CI engine fueled with safflower methyl ester (SAME). Retarded timing reduced NO_x by 28%, along with CO and smoke, but lowered BTE by 10%. Advanced timing slightly increased NO_x while reducing smoke opacity. The study highlights the importance of injection timing optimization to mitigate high viscosity effects and enhance engine performance and emissions [8].

With the increasing focus on emission regulations and design innovations in internal combustion engines, the effects of different oils and production methods used in biodiesel have gained importance in terms of engine performance. In this context, engine operating behavior across speed-load ranges, emissions, fuel consumption, noise, mechanical load, and thermal load are frequently used to define engine performance [9].

The cetane number, flash point, viscosity, lubricating properties, thermal properties, physical characteristics and molecular structure of the fuel influence changes in engine vibration [10]. The combustion noise level is affected by the rate of increase in combustion pressure, which is, in turn, related to parameters such as injection timing and ignition delay [11]. A considerable number of studies have focused on dynamic response characteristics specifically noise and vibration profiles of internal combustion engines operating on biodiesel, aiming to assess its impact on acoustic performance and structural integrity.

Susilo et al. tested diesel-essential oil blends (5–20%) on a 402 CC Dongfeng engine at 1,300–1,900 rpm. The B10 blend at 1,300 rpm showed the longest fuel consumption time (155 s) with lowest noise (105.7 dB) and vibration (975.7 Hz). The B20 blend achieved the lowest exhaust emissions (56.8%). Results indicate essential oil blends reduce noise and vibration while influencing fuel efficiency and emissions. [12].

Al-Rawashdeh et al. studied carbonyl emissions from a CI engine using diesel and methanol/diesel blends (DM10, DM20). Methanol blends raised aldehyde emissions, especially at low loads, but lowered NO_x, HC, and CO at high speeds. DM20 had the lowest NO_x due to charge cooling. Formaldehyde decreased with load, while acrolein and crotonaldehyde increased. Higher methanol reduced power and torque but improved combustion cleanliness, raising concerns about toxic aldehydes. [13].

Ala'a et al. investigated the extraction, characterization and engine performance of muskmelon seed oil biodiesel in various blends (BD₁₀, BD₂₀, BD₅₀ and BD₁₀₀). Produced via esterification and transesterification, the biodiesel was tested in a single-cylinder diesel engine across multiple speeds. BD₂₀ exhibited the best performance with brake thermal efficiency (36.0%)

nearly equal to diesel and lower CO (207 ppm) and SO₂ emissions. Though BD₁₀₀ showed the highest NO_x, BD₂₀ had optimal emission balance. Physical tests confirmed compliance with biodiesel standards. This study suggests BD₂₀ as a sustainable, engine-compatible fuel from agricultural waste, reducing environmental pollution while promoting renewable energy in semi-arid regions like Jordan [14].

Al-Hwaiti et al. produced biodiesel from Handal oil using catalysts NaOH, KOH, NaOCH₃, and Fe₂O₃ nano. Sodium methoxide (NaOCH₃) gave the highest yield (99.4%). Engine tests with B20 and B80 blends showed B80 improved brake power and reduced CO and HC emissions, with a slight NO_x increase. Fe₂O₃ nano catalysts were efficient and reusable. The study supports Handal biodiesel as a sustainable fuel with good performance and emission benefits, especially for arid regions like Jordan [15].

Biodiesel has a high oxygen content, which causes combustion in biodiesel blends to start earlier and spread more evenly [16]. The oxygen concentration in fuels plays a crucial role in reducing emissions of carbon dioxide, carbon monoxide and particulate matter [17]. According to many researchers, it is a general trend that biodiesel and its blends generate higher combustion noise compared to conventional mineral diesel [18]. Since biofuel is a highly viscous fuel, using pure vegetable oil in diesel engines is expected to cause various problems such as poor atomization, advanced injection, injector blockages and piston ring sticking [19]. The engine noise was measured as Sound Pressure Level (SPL) and this measurement was performed using Eq (1).

P_{RMS}: RMS value of the sound pressure measured from the microphone

P₀: Reference sound pressure value

$$\text{Sound Pressure Level (SPL)} = 20 \log_{10} \left(\frac{P_{RMS}}{P_0} \right) \text{dB} \quad (1)$$

Results of all the parameters of biodiesel are well within the standard range of ASTM standards, comparable with that of normal diesel, and hence the biodiesel is suitable for use in CI engine as a fuel [20]. Patnaik et al. conducted research highlighting the use of artificial neural networks (ANN) to enhance the integration of biodiesel in compression ignition (CI) engines. With optimized topologies like 6-5-1 for Brake-Specific Fuel Consumption (BSFC). ANN accurately predicted biodiesel performance and emissions, showing low mean squared errors (MSE) and high correlation coefficients. The findings advocate for broader adoption of biodiesel in alignment with global clean energy and sustainability goals [21].

Hosseini et al. evaluated the impact of alumina nanoparticles on diesel-biodiesel blends using an artificial neural network (ANN) to predict engine performance, emissions and vibration. An

ANN model with a 12-25-25-12 architecture, trained via the Levenberg-Marquardt algorithm, demonstrated high accuracy, with R-values of 0.97–0.99 for performance and emissions predictions, and 0.94–0.99 for vibration analysis. The study confirms that the ANN method effectively correlates predicted data with experimental results, showing the potential of nano-catalysts to improve biodiesel's thermo-physical properties and engine efficiency [22].

Çelebi et al. studied the effects of biodiesel blends (20%, 40% sunflower and canola) and natural gas on noise and vibration in an unmodified diesel engine. Biodiesel reduced SPL and vibration and lowered CO emissions but increased CO₂ and NO_x. Natural gas further reduced noise and emissions but worsened overall emissions. An ANN model accurately predicted SPL and vibration, outperforming linear regression. The study highlights biodiesel's noise reduction benefits with emission trade-offs [23].

Yıldırım et al. compared ANN and SVM for predicting vibration, noise, and emissions (CO, CO₂, NO_x) in a diesel engine fueled with biodiesel blends and hydrogen. ANN with Levenberg-Marquardt training outperformed SVM, achieving higher R² and lower MAPE across all parameters. SVM showed weaker performance, especially in CO prediction [24].

This study innovatively evaluates the effects of safflower methyl ester on diesel engines, covering energy analysis, performance, noise emissions, and uses artificial neural networks (ANN) to predict experimental data. It uniquely examines different transfer functions and training algorithms to improve ANN accuracy from multiple measurement points, contributing to advanced engine data modeling. The approach integrates environmental impact and engine compatibility of alternative fuels. Key assumptions include stable environmental conditions, consistent fuel properties, and calibrated measurement devices ensuring accurate data. ANN models assume a continuous, learnable relationship between inputs and outputs, with training/testing data being representative and independent. Min-max normalization is valid, assuming stable data ranges, and datasets are free of outliers. These assumptions underpin the reliability of experimental results and ANN predictions.

2. Material and Methods

In this study, safflower methyl ester (SME) was produced via a base-catalyzed transesterification process. Specifically, safflower oil reacted with methanol at a concentration of 20% by volume, using sodium hydroxide (3.5 g per liter of oil) as the alkaline catalyst. The reaction was carried out under controlled conditions to ensure efficient conversion of triglycerides into methyl esters, resulting in a biodiesel fuel suitable for engine performance evaluation. Euro diesel was obtained from the market. The test engine is a single cylinder, water

cooled, 17:1 compression ratio, 15 HP, 60 Nm torque diesel engine. A Jetronl S4001 noise level meter with a measurement range of 30-130 dB and a sensitivity of 1.5 dB was used to measure the noise levels. Measurements were taken from four different points of the engine at a distance of one meter. The results of the analysis of the test fuels are presented in Table 1. The values in the table comply with the EN 590 standard for Euro diesel fuel and the EN 14214 standard for safflower methyl ester fuel.

2.1. Energy Analysis

In general, energy analysis is defined as the energy supplied and consumed within the system. This analysis enables the measurement of the internal energy difference and enthalpy due to mass flow, as a function of the transfer of energy between points in cycles, either as heat or useful work. Thermodynamic analysis paves the way for studying test fuel mixtures and various operating conditions in comparison with basic engine operation. The effect of various factors, such as engine load and mixed fuel conditions, helps to calculate losses during the investigation process [25].

Engine energy analysis calculations are given in Equation (2) through Equation (5).

To facilitate computational simplicity before implementation on the test engine, the following assumptions were considered:

- The engine operation is assumed to be in steady state.
- The air and exhaust gases of the engine are considered ideal gases [26].

Energy analysis enables the quantification of energy transformations, such as work and heat, within a control volume by evaluating energy transfers and the enthalpy associated with mass flow across its boundaries [27].

$$\sum \dot{m}_{in} = \sum \dot{m}_{out} \quad (2)$$

$\dot{m}_{in}$: Mass of air and fuel mixture entering the interior

$\dot{m}_{out}$: Mass of exhaust gases at the outlet

$$\dot{E}_{fuel} = \dot{W} + \dot{Q}_{lost} \quad (3)$$

$\dot{E}_{fuel}$: Fuel energy ratio

$\dot{W}$: Brake Power

$\dot{Q}_{lost}$: Lost energy rate

$$\dot{E}_{fuel} = \dot{m}_{fuel} \cdot H_u \quad (4)$$

$\dot{m}_{fuel}$: Mass flow rate

H_u : Low calorific value

$$\dot{W} = \frac{\pi \cdot n \cdot \tau}{30} \quad (5)$$

n : Motor speed

τ : Engine torque

3. Conclusion and Discussion

3.1. Engine Performance

The torque variation obtained at different engine speeds during full-load tests with Euro diesel fuel and safflower methyl ester is illustrated in Figure 1 as a function of engine speed. The maximum torque was measured at 54.957 Nm at 1200 rpm using D₁₀₀ fuel. A decrease of 0.34% in torque was observed with B₁₀₀ fuel compared to D₁₀₀ fuel. The primary reason for the higher torque values in D₁₀₀ fuel compared to those of the other fuels is that the kinematic viscosity of D₁₀₀ fuel is lower than that of B₁₀₀ fuel, as shown in Table 1.

The changes in the effective power values obtained at different engine speeds during full-load tests using Euro diesel and safflower methyl ester fuels are presented in Figure 2.

The maximum engine power was measured at 14.467 HP at 2000 rpm using D₁₀₀ fuel. A decrease of 2.5% was observed with B₁₀₀ fuel compared to D₁₀₀ fuel. This reduction is attributed to insufficient atomization and low ignition quality due to the high density of B₁₀₀, as indicated in Table 1. The changes in specific fuel consumption values obtained at different engine speeds during full-load tests using Euro diesel and safflower methyl ester fuels are presented in Figure 3. The minimum specific fuel consumption was measured at 231.955 g/HP-h at 1500 rpm for D₁₀₀ fuel. An increase of 4.78% in specific fuel consumption was observed with B₁₀₀ fuel compared to D₁₀₀ fuel.

The changes in fuel consumption values obtained at different engine speeds during full-load tests using Euro diesel and safflower methyl ester fuels are illustrated in Figure 4. At the maximum engine power of 2000 rpm, the fuel consumption value for D₁₀₀ fuel was measured at 1.009 g/h. The oxygen in biodiesel and additives causes fuel premixed phase combustion, which improves thermal efficiency and combustion [28]. An increase of 10.07% was observed for B₁₀₀ fuel compared to D₁₀₀ fuel. The primary reason for the higher specific fuel consumption and fuel consumption values in B₁₀₀ fuel compared to D₁₀₀ fuel is that the calorific value of B₁₀₀ is lower, as shown in Table 1. The analysis of engine torque, brake power, specific fuel consumption, and total fuel consumption demonstrates consistency with the results presented by Borecki et al. [29].

3.2. Noise Emissions

In internal combustion engines, the formation of vibrations is largely dependent on the magnitude and rate of mechanical forces within the cylinder. According to the experimental data obtained in this study, maximum in-cylinder pressure, heat release rate, and pressure rise

rate generate vibrations throughout the engine cycle. Noise emissions, which are a consequence of these vibrations, exhibit a similar trend [30]. Furthermore, when the engine is under load, increased friction between the crankshaft bearings, cylinder-piston surfaces, and other engine components, along with the elevated combustion pressure inside the cylinder, contributes to higher levels of noise emissions [31]. Therefore, analyses were conducted under different load conditions in this study.

Figure 5 displays the noise emission graph measured at one meter from point A as a function of engine speed. An analysis of the graph reveals a 0.102% decrease in noise emission for B₁₀₀ fuel at maximum engine power at 2000 rpm compared to D₁₀₀ fuel. Figure 6 presents the noise emission graph measured one meter from point B as a function of engine speed. An analysis of the graph indicates a 0.103% decrease in noise emission for B₁₀₀ fuel at maximum engine power at 2000 rpm compared to D₁₀₀ fuel. Figure 7 illustrates the noise emission graph of the fuels measured at one meter from point C as a function of engine speed. An analysis of the graph reveals a 0.102% decrease in noise emission for B₁₀₀ fuel at maximum engine power at 2000 rpm compared to D₁₀₀ fuel. Figure 8 displays the noise emission graph of the fuels measured one meter from point D as a function of engine speed. An analysis of the graph indicates a 0.102% decrease in noise emission for B₁₀₀ fuel at maximum engine power at 2000 rpm compared to D₁₀₀ fuel. Upon analyzing the graph, a decrease in noise emission is observed for B₁₀₀ fuel compared to D₁₀₀ fuel. This reduction is attributed to the high kinematic viscosity values of B₁₀₀ fuel and the damping effect provided by the lubricating properties of safflower methyl ester, as indicated in Table 1. In this research, it is assumed that as the speed of the machines increases, the time to complete jobs is reduced, but the noise pollution in the production environment is increased [32]. The results obtained from the analysis of the noise emission values following engine tests are consistent with the findings of Ahmed et al. [33] and Sanjid et al. [34].

3.3. Energy Analysis

The outcomes of the energy analysis conducted on the fuel samples at different engine speeds are summarized below, with Figure 9 illustrating the results obtained at 1200 rpm. Which corresponds to the maximum torque speed; Figure 10 shows the results at 1500 rpm. representing the minimum brake specific fuel consumption speed; Figure 11 displays the results at 2000 rpm. associated with the maximum power speed. Increasing the brake power of pure diesel and oxygenated fuel mixtures enhanced the thermal efficiency of the brakes [35].

It was determined that for all fuels, the fuel energy flow increased with rising engine speed. The primary reason for the higher energy analysis values of D₁₀₀ fuel compared to B₁₀₀ fuel is the lower calorific value of B₁₀₀ fuel, as indicated in Table 1. The results obtained from the examination of the energy analysis values because of engine tests aligned with the findings of the studies conducted by Kul and Kahraman [36].

3.4. Investigation of Noise Emission Prediction with ANN Model

Artificial Neural Networks (ANN) provide flexible architectures that are particularly effective in addressing nonlinear problems. ANN provides effective process modeling in terms of efficiency, accuracy, and cost [37]. ANN models offer flexibility and powerful learning capabilities for large and complex datasets; they learn non-linear patterns in data thanks to their multi-layered structure [38]. Artificial neural network architecture consists of several layers, with each one linked to its successor. Every layer is comprised of neurons or processing elements, each equipped with a nonlinear activation function, excluding those at the input level [39]. This iterative process continues until the neural network output aligns with the target output. Therefore, it is essential for an artificial neural network model to be trained, tested, and validated based on a substantial amount of data [40]. In the present study, the Feed-Forward Back-Propagation (FFBP) model, a widely utilized ANN approach for addressing nonlinear problems, is employed. Predictions were made for the four different points of noise emissions obtained using an artificial neural network (ANN) model. The training and testing data were separated with an 80% training and 20% testing ratio. Figure 12 shows the ANN architecture.

3.4.1. Error Analysis

Three different constraint methods are commonly employed in neural network predictions. These constraints facilitate the evaluation of the model's success by examining the difference between predicted values and actual values. The mathematical models representing these constraints are presented below. Their primary aim is to minimize errors and optimize prediction performance to enhance the model's accuracy. The equations for the error metrics are provided in Equations (6) through Equations (8) below. The Root Mean Square Error (RMSE) is one such metric. RMSE (Root Mean Square Error) is a metric that measures the square root of the average squared differences between predicted and actual values. It indicates how much prediction errors deviate from the real values.

n = total number of observations (dimensionless)

e_t = error at time t. calculated as the difference between the observed value and the predicted value at time t (same unit as the predicted variable)

t = time index or observation index. running from 1 to n (dimensionless)

$$\sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2} \quad (6)$$

Mean-Square Error (MSE)

This formula calculates the Mean-Square Error (MSE). which measures the average of the squared differences between predicted and actual values.

n: number of observations (unitless)

e_t : error at time t (same unit as the predicted variable)

$$\frac{1}{n} \sum_{t=1}^n e_t^2 \quad (7)$$

Mean Absolute Percentage Error (MAPE) [41]

MAPE (Mean Absolute Percentage Error) is a metric that measures the average absolute error between predicted and actual values. expressed as a percentage of the actual values.

n: number of observations (unitless)

e_t : absolute error at time t (i.e.. $|\text{predicted}_t - \text{actual}_t|$)

v_t : actual value at time

MAPE: the result is expressed as a percentage (%)

A lower MAPE value indicates better model accuracy with 0% being perfect prediction

$$\frac{\%100}{n} \sum_{t=1}^n \frac{e_t}{v_t} \quad (8)$$

Compute performance metrics such as MSE, RMSE and Accuracy Rates to quantify the model's predictive accuracy and effectiveness [42]. Concerning the performance of forecasting models. the values of RMSE. MSE. and MAPE should ideally be close to zero. To evaluate a linear relationship. the R^2 correlation coefficient should be as close to 1 as possible. indicating that the model possesses strong predictive capability.

3.4.2. Data analysis

The data were collected from experiments conducted on an experimental compression ignition (CI) engine assembly operating at specific speeds of 1000, 1500, 1900 and 2400 rpm. The experiments were carried out separately for B₁₀₀ and D₁₀₀ fuels. Energy analysis, engine performance and noise emission tests were performed during the experiments. Noise emissions were measured from four different points on the engine using a Jetronl S4001 noise level meter. The dataset includes parameters such as engine speed (RPM). engine torque (Nm), power (Bg),

fuel consumption (g/s), specific fuel consumption (g/Bg), fuel consumption (kg/s) and fuel energy flow (Bg). These parameters were utilized to estimate the noise emissions obtained from the four different points separately using an artificial neural network (ANN) model. When estimating noise emissions at point A, data from the other points (B, C and D) were also included in the input data. The same approach was applied to points B, C and D. The same models were employed to analyze the data while predicting each of the four points respectively. The dataset was divided into 80% for training and 20% for testing. Additionally, the data were normalized to address the imbalance between the values of 1 and 0. Consequently, the success rates of the raw and normalized data were also evaluated.

Normalization is a data transformation technique employed to convert a wide range of digital values in a dataset into a common measurement while preserving proportional differences. Various normalization techniques are available, with min-max normalization being the most common [43]. The following equation Eq (9) is used as the formula for min-max normalization. Min-max normalization is a technique used to scale data between 0 and 1. The following formula is used:

x : the original data value

$x_{\min}$: the minimum value in the dataset

$x_{\max}$: the maximum value in the dataset

x_{norm} : the normalized value (unitless, ranges from 0 to 1)

This method ensures all values are scaled proportionally within the range [0, 1], which improves the performance of many machine learning models.

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (9)$$

3.4.3. Modelling Artificial Neural Networks

Three training algorithms TrainLM (Levenberg-Marquardt), TrainBR (Bayesian Regularization), and TrainBFGS (Broyden-Fletcher-Goldfarb-Shanno) were used for noise emission estimation. The number of neurons and layers was fixed, while epochs varied based on testing success. TrainLM is fast and accurate for small to medium datasets, using Newton derivatives for efficient weight updates. TrainBR extends TrainLM with regularization to reduce overfitting, improving generalization on noisy data. TrainBFGS, a Gauss-Newton method, requires second derivatives and solves linear equations each iteration, offering high precision and faster convergence for large datasets. The ANN employed multilayer perceptron

(MLP) architecture with three transfer functions tested: pure linear (Pure-Lin), log sigmoid (Log-Sig), and hyperbolic tangent sigmoid (Tan-Sig) to find the optimal network structure.

3.4.4. Evaluation of Artificial Neural Network Results

In this study, noise emissions at four different measurement points were estimated using five distinct ANN models per point, for both diesel (D_{100}) and biodiesel (B_{100}) fuels. A total of 80 models were developed using both raw and normalized datasets. The prediction performances were assessed using RMSE, MSE, and MAPE metrics. As shown in Table 2, for D_{100} , the most successful model using raw data was the TRAINBR algorithm at point A, with a 2-layer, 15-neuron ANN architecture employing the Pure-Lin transfer function (RMSE: 2.432, MSE: 5.914, MAPE: 2.279). For normalized data, the most accurate result was obtained at point A with the TRAINBFG algorithm using the same architecture (RMSE: 0.214, MSE: 0.046, MAPE: 21.53). In general, non-normalized data produced superior results.

Similarly, Table 3 presents B_{100} results. The best-performing model with raw data at point A was obtained using the TRAINLM algorithm with 1 layer, 10 neurons, and the Tan-Sig transfer function (RMSE: 1.149, MSE: 1.321, MAPE: 0.997). For normalized B_{100} data, the top result was achieved using TRAINBR with 2 layers, 15 neurons, and the Pure-Lin function (RMSE: 0.023, MSE: 0.001, MAPE: 4.004). Again, raw data generally led to higher prediction accuracy. Figures 13 to 16 illustrate the best-performing models for each fuel type and normalization state across all measurement points, consistently highlighting point A as the location with the highest accuracy. This success is attributed to the low variance of data at point A, which facilitates more effective learning, particularly when using linear transfer functions such as Pure-Lin and algorithms like TRAINBR and TRAINLM. Overall, the study shows that models trained on raw data tend to generalize better due to the greater variance in the dataset. Figure 17 compares the error metrics of the best models across both D_{100} and B_{100} , confirming the advantage of raw data. TRAINBR, due to its Bayesian regularization, performs well on noisy or complex datasets by mitigating overfitting risks, unlike TRAINLM which, while faster, may overlearn in such conditions. The study emphasizes that model performance is highly dependent on dataset-specific features. The use of four distinct datasets in this research revealed that TRAINLM, TRAINBR, and TRAINBFG each outperform the others under different conditions, underscoring the importance of model selection based on data characteristics. The architecture of the best B_{100} model using TRAINLM (1 layer, 10 distributions, Tan-Sig) is shown in Figure 18.

Traditional methods have proven insufficient for managing large datasets, prompting the development of advanced ML techniques that leverage atmospheric attributes to enhance prediction accuracy and minimize errors [44]. After evaluating the weights of the features, it is important to determine the feature selection algorithm [45]. Solving it using machine learning-based approaches may lead to promising results [46].

4. Conclusion

This study investigated the performance, energy analysis, and noise emissions of D₁₀₀ and laboratory-produced B₁₀₀ fuels in a CI diesel engine. Experimental data showed that while D₁₀₀ offered superior engine performance and energy efficiency, B₁₀₀ exhibited lower noise emissions, highlighting its environmental advantage. Noise data were collected at four engine speeds and four measurement points using a Jetronl S4001 device. Engine parameters included speed, torque, power, fuel consumption, and energy flow. ANN models were trained using TrainLM, TrainBR, and TrainBFG algorithms, with model performance evaluated via RMSE, MSE, MAPE, and R² metrics. Early stopping and data splitting (80% training, 20% testing) were applied to prevent overfitting. Among 80 tested configurations, the most accurate predictions were consistently achieved at point A. For raw D₁₀₀ data, TRAINBR with a 2-layer, 15-neuron Pure-Lin setup performed best, while normalized data favored TRAINBFG. For B₁₀₀, TRAINLM (1 layer, 10 neurons, Tan-Sig) excelled in raw data, whereas TRAINBR yielded the best results with normalized inputs. Overall, non-normalized data improved generalization due to higher variance, while low-variance data enabled more effective learning. TrainBR demonstrated superior robustness in noisy datasets, whereas TrainLM offered speed and precision with potential overfitting risks. These findings emphasize that model success depends heavily on data structure and the selection of suitable algorithms and transfer functions. Future research may explore different neuron/layer configurations to enhance model optimization and contribute to environmentally conscious engine technology development.

Credit Authorship Contribution Statement

Fatih Aydın: Formal analysis. original draft. software. supervision. conceptualization. methodology. **Büşra Nur Çayan:** Software – methodology. formal analysis.

Authors' Conflicts of Interest

There are no financial interests or personal relationships that may have affected the work in this article.

Data availability statement

Authors do not have permission to share data.

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Table List

Table 1. Analysis of Fuels

Features	Units	B ₁₀₀	D ₁₀₀	Limiting Values	
				Euro diesel	Safflower Methyl Ester
Density (15°C)	g/cm ³	0.885	0.843	0.82-0.84	0.86-0.90
Kinematic Viscosity (40°C)	mm ² /s	4.32	3.31	2- 4.5	3.5-5
Flash Point	°C	120	60	55	101
Water Content	ppm	395	39	200	500
pH	—	5.2	5.3	—	—
Thermal Value	kJ/kg	40865	47645	—	—
Cloud Point	°C	-3	-8	—	—
Pour Point	°C	-8.5	-19	—	—
Freezing Point	°C	-12.4	<-20	—	—
CFPP	°C	-8	-18	- 20	-15
Copper Strip Corrosion	—	1a	1a	No:1	No:1
Cetan	—	45	56	51	—

Table 2. Diesel data and normalized diesel data estimates at 4 different noise points

	Data	Output	Transfer Function	Model	Network Architecture	Training	Test	Training	Test	Training	Test
						RMSE	RMSE	MSE	MSE	MAPE	MAPE
REAL DATE	D100	A	Tan-Sig	TRAINLM	10-10-1	1.965	4.653	3.861	21.65	1.153	4.108
	D100	A	Pure-Lin	TRAINLM	10-15-15-1	0.259	5.955	0.067	35.46	0.202	4.944
	D100	A	Log-Sig	TRAINLM	10-20-20-1	0.256	8.746	0.066	76.49	0.119	7.460
	D100	A	Pure-Lin	TRAINBR	10-15-15-1	0.376	2.432	0.141	5.914	0.239	2.279
	D100	A	Pure-Lin	TRAINBFG	10-15-15-1	2.566	8.737	6.585	76.34	2.161	7.327
	D100	B	Tan-Sig	TRAINLM	10-10-1	0.434	2.649	0.188	7.017	0.375	2.423
	D100	B	Pure-Lin	TRAINLM	10-15-15-1	0.335	2.506	0.112	6.281	0.252	2.277
	D100	B	Log-Sig	TRAINLM	10-20-20-1	0.244	10.10	0.060	101.9	0.097	9.871
	D100	B	Pure-Lin	TRAINBR	10-15-15-1	2.358	5.564	5.558	30.96	2.198	5.370
	D100	B	Pure-Lin	TRAINBFG	10-15-15-1	0.815	2.506	0.665	6.279	0.646	2.276
	D100	C	Tan-Sig	TRAINLM	10-10-1	0.369	5.598	0.136	31.33	0.189	4.922
	D100	C	Pure-Lin	TRAINLM	10-15-15-1	0.250	9.060	0.063	82.08	0.156	7.833
	D100	C	Log-Sig	TRAINLM	10-20-20-1	0.473	2.865	0.224	8.207	0.295	2.598

NORMALIZED DATE	D100	C	Pure-Lin	TRAINBR	10-15-15-1	0.318	2.772	0.101	7.684	0.226	2.576
	D100	C	Pure-Lin	TRAINBFG	10-15-15-1	2.220	9.123	4.930	83.23	1.961	7.619
	D100	D	Tan-Sig	TRAINLM	10-10-1	0.208	4.078	0.043	16.63	0.173	3.643
	D100	D	Pure-Lin	TRAINLM	10-15-15-1	0.342	3.000	0.117	9.000	0.260	2.778
	D100	D	Log-Sig	TRAINLM	10-20-20-1	0.580	7.503	0.336	56.29	0.271	5.658
	D100	D	Pure-Lin	TRAINBR	10-15-15-1	0.410	3.010	0.168	9.061	0.248	2.792
	D100	D	Pure-Lin	TRAINBFG	10-15-15-1	0.264	2.933	0.070	8.604	0.209	2.680
	D100	A	Tan-Sig	TRAINLM	10-10-1	0.038	0.495	0.001	0.704	10.32	77.17
	D100	A	Pure-Lin	TRAINLM	10-15-15-1	0.027	0.720	0.001	0.518	8.856	64.67
	D100	A	Log-Sig	TRAINLM	10-20-20-1	0.027	0.412	0.001	0.170	6.946	44.91
	D100	A	Pure-Lin	TRAINBR	10-15-15-1	0.025	0.236	0.001	0.056	7.735	25.70
	D100	A	Pure-Lin	TRAINBFG	10-15-15-1	0.023	0.214	0.001	0.046	7.350	21.53
	D100	B	Tan-Sig	TRAINLM	10-10-1	0.037	0.124	0.001	0.351	11.70	35.76
	D100	B	Pure-Lin	TRAINLM	10-15-15-1	0.047	0.906	0.002	0.821	11.85	100.0
	D100	B	Log-Sig	TRAINLM	10-20-20-1	0.050	0.222	0.003	0.049	12.41	22.40
	D100	B	Pure-Lin	TRAINBR	10-15-15-1	0.028	0.906	0.001	0.821	8.523	100.0
	D100	B	Pure-Lin	TRAINBFG	10-15-15-1	0.001	0.049	0.032	0.222	9.789	22.39
	D100	C	Tan-Sig	TRAINLM	10-10-1	0.029	0.727	0.001	0.528	9.720	80.61
	D100	C	Pure-Lin	TRAINLM	10-15-15-1	0.039	0.897	0.002	0.805	12.33	100.0
	D100	C	Log-Sig	TRAINLM	10-20-20-1	0.022	0.270	0.000	0.073	7.705	27.40
	D100	C	Pure-Lin	TRAINBR	10-15-15-1	0.195	0.492	0.038	0.242	70.75	53.75
	D100	C	Pure-Lin	TRAINBFG	10-15-15-1	0.023	0.897	0.001	0.805	6.606	100.0
	D100	D	Tan-Sig	TRAINLM	10-10-1	0.034	0.350	0.001	0.122	11.06	34.97
	D100	D	Pure-Lin	TRAINLM	10-15-15-1	0.153	0.239	0.024	0.057	23.29	24.39
	D100	D	Log-Sig	TRAINLM	10-20-20-1	0.035	0.474	0.001	0.225	11.23	51.37
	D100	D	Pure-Lin	TRAINBR	10-15-15-1	0.027	0.239	0.001	0.057	7.494	24.39
	D100	D	Pure-Lin	TRAINBFG	10-15-15-1	0.030	0.239	0.001	0.057	8.431	24.39

Table 3. Biodiesel data and normalized biodiesel data estimates at 4 different noise points

	Data	Output	Transfer Function	Model	Network Architecture	Training	Test	Training	Test	Training	Test
						RMSE	RMSE	MSE	MSE	MAPE	MAPE
REAL DATE	B100	A	Tan-Sig	TRAINLM	10-10-1	0.258	1.149	0.067	1.321	0.150	0.977
	B100	A	Pure-Lin	TRAINLM	10-15-15-1	0.377	0.204	0.142	0.042	0.223	4.151
	B100	A	Log-Sig	TRAINLM	10-20-20-1	0.283	5.596	0.080	31.320	0.164	4.180
	B100	A	Pure-Lin	TRAINBR	10-15-15-1	0.151	1.594	0.023	2.541	0.117	1.102
	B100	A	Pure-Lin	TRAINBFG	10-15-15-1	1.307	0.016	1.709	0.000	0.867	0.013
	B100	B	Tan-Sig	TRAINLM	10-10-1	0.422	3.260	0.178	10.627	0.240	2.914
	B100	B	Pure-Lin	TRAINLM	10-15-15-1	0.359	3.589	0.129	12.881	0.203	3.234

NORMALIZED DATE	B100	B	Log-Sig	TRAINLM	10-20-20-1	0.516	3.198	0.266	10.225	0.272	2.869
	B100	B	Pure-Lin	TRAINBR	10-15-15-1	0.409	3.365	0.167	11.321	0.303	3.125
	B100	B	Pure-Lin	TRAINBFG	10-15-15-1	0.266	3.230	0.071	10.433	0.230	2.934
	B100	C	Tan-Sig	TRAINLM	10-10-1	0.414	9.334	0.171	87.130	0.203	7.849
	B100	C	Pure-Lin	TRAINLM	10-15-15-1	0.337	2.726	0.113	7.432	0.236	2.464
	B100	C	Log-Sig	TRAINLM	10-20-20-1	0.334	8.473	0.111	71.792	0.157	7.104
	B100	C	Pure-Lin	TRAINBR	10-15-15-1	0.269	2.748	0.072	7.552	0.178	2.507
	B100	C	Pure-Lin	TRAINBFG	10-15-15-1	0.440	2.723	0.193	7.413	0.344	2.457
	B100	D	Tan-Sig	TRAINLM	10-10-1	0.183	2.509	0.034	6.293	0.156	2.278
	B100	D	Pure-Lin	TRAINLM	10-15-15-1	0.204	2.514	0.041	6.319	0.174	2.291
	B100	D	Log-Sig	TRAINLM	10-20-20-1	0.258	8.608	0.067	74.091	0.121	7.515
	B100	D	Pure-Lin	TRAINBR	10-15-15-1	0.240	2.530	0.057	6.400	0.157	2.322
	B100	D	Pure-Lin	TRAINBFG	10-15-15-1	0.987	8.547	0.975	73.058	0.728	7.179
	B100	A	Tan-Sig	TRAINLM	10-10-1	0.003	0.139	0.000	0.019	8.094	10.050
	B100	A	Pure-Lin	TRAINLM	10-15-15-1	0.017	0.000	0.000	0.000	46.028	0.023
	B100	A	Log-Sig	TRAINLM	10-20-20-1	0.028	0.023	0.001	0.001	13.084	1.937
	B100	A	Pure-Lin	TRAINBR	10-15-15-1	0.026	0.023	0.001	0.001	4.004	1.683
	B100	A	Pure-Lin	TRAINBFG	10-15-15-1	0.052	0.017	0.003	0.000	14.552	1.307
	B100	B	Tan-Sig	TRAINLM	10-10-1	0.037	0.351	0.001	0.124	11.703	35.761
	B100	B	Pure-Lin	TRAINLM	10-15-15-1	0.047	0.906	0.002	0.821	11.851	100.000
	B100	B	Log-Sig	TRAINLM	10-20-20-1	0.050	0.222	0.003	0.049	12.413	22.403
	B100	B	Pure-Lin	TRAINBR	10-15-15-1	0.028	0.906	0.001	0.821	8.523	100.000
	B100	B	Pure-Lin	TRAINBFG	10-15-15-1	0.032	0.049	0.001	0.222	9.789	22.392
	B100	C	Tan-Sig	TRAINLM	10-10-1	0.023	0.514	0.001	0.264	8.797	49.040
	B100	C	Pure-Lin	TRAINLM	10-15-15-1	0.018	0.227	0.000	0.052	5.771	22.823
	B100	C	Log-Sig	TRAINLM	10-20-20-1	0.232	0.000	0.054	0.013	5.023	23.584
	B100	C	Pure-Lin	TRAINBR	10-15-15-1	0.559	0.184	0.313	0.034	61.376	81.449
	B100	C	Pure-Lin	TRAINBFG	10-15-15-1	0.016	0.228	0.000	0.052	5.821	23.117
	B100	D	Tan-Sig	TRAINLM	10-10-1	0.024	0.456	0.001	0.208	8.251	43.637
	B100	D	Pure-Lin	TRAINLM	10-15-15-1	0.017	0.228	0.000	0.052	6.426	22.987
	B100	D	Log-Sig	TRAINLM	10-20-20-1	0.060	0.763	0.004	0.583	12.426	74.469
	B100	D	Pure-Lin	TRAINBR	10-15-15-1	0.184	0.559	0.034	0.313	88.364	61.409
	B100	D	Pure-Lin	TRAINBFG	10-15-15-1	0.017	0.229	0.000	0.052	6.645	23.106

Figure List

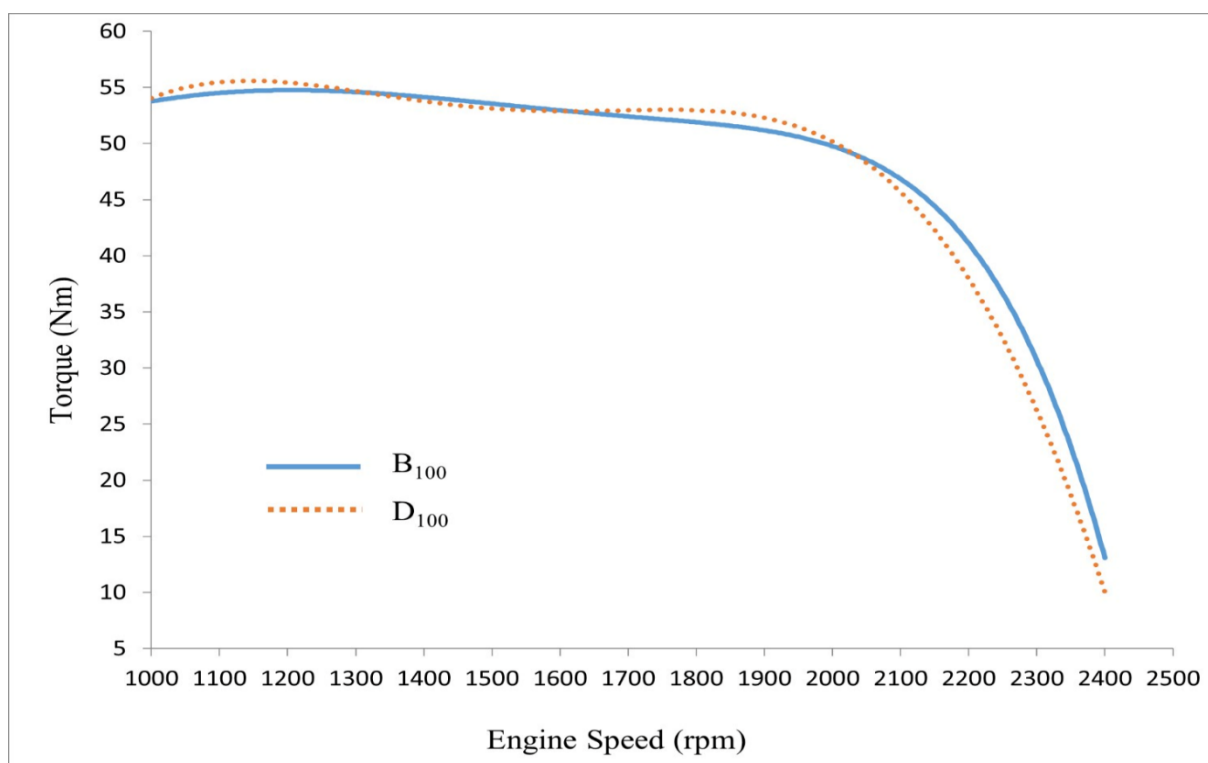


Figure 1. Engine torque values depending on the engine speed

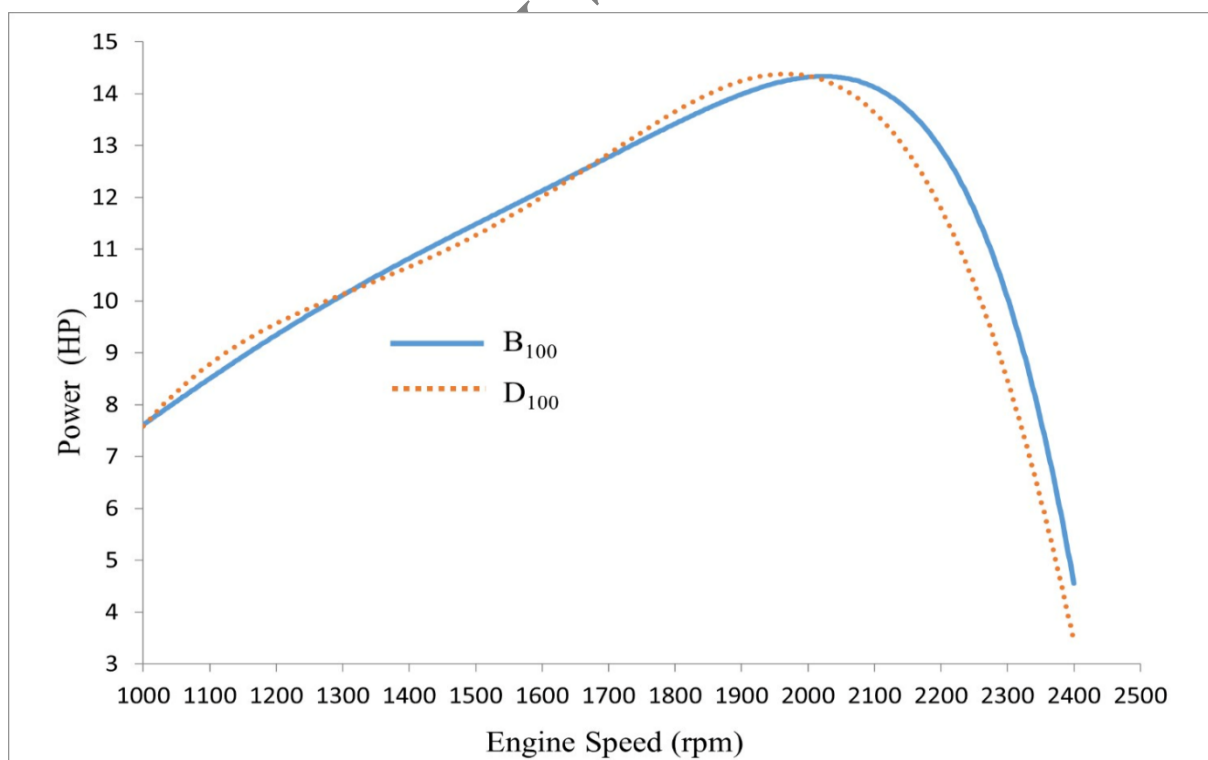


Figure 2. Engine power ratings depending on engine speed

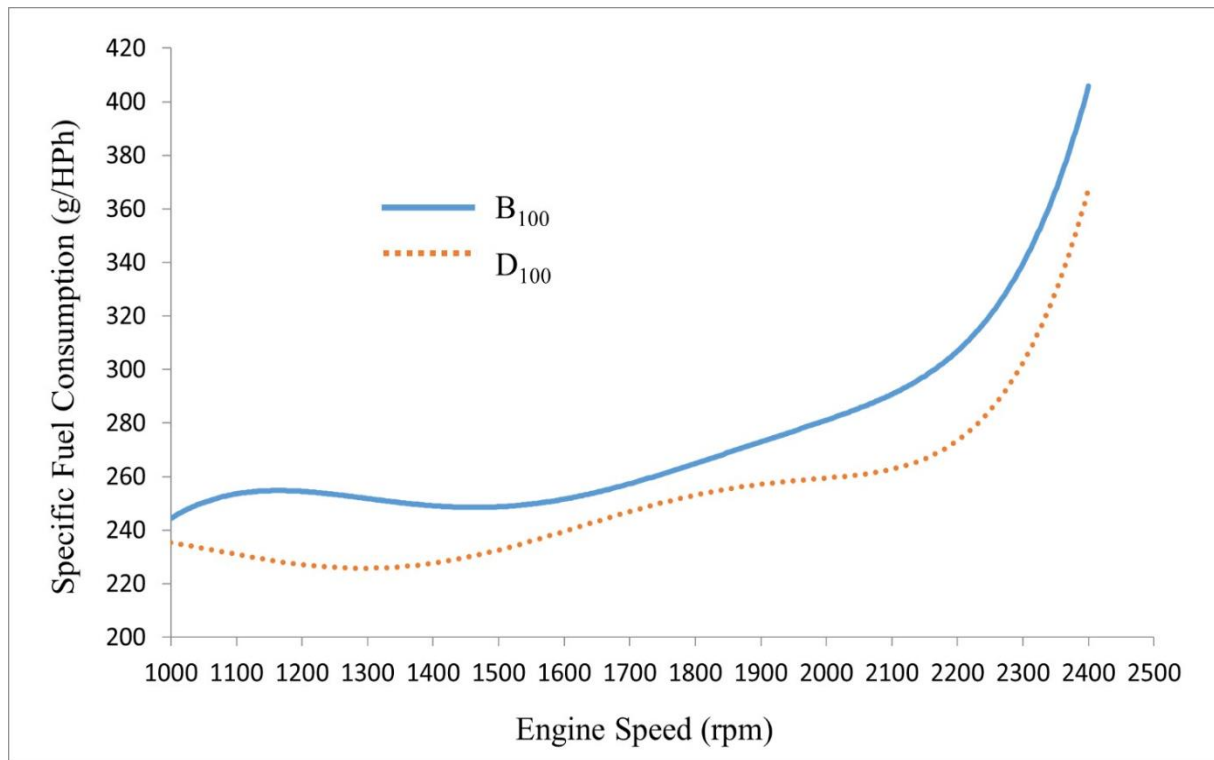


Figure 3. Specific fuel consumption values depending on engine speed

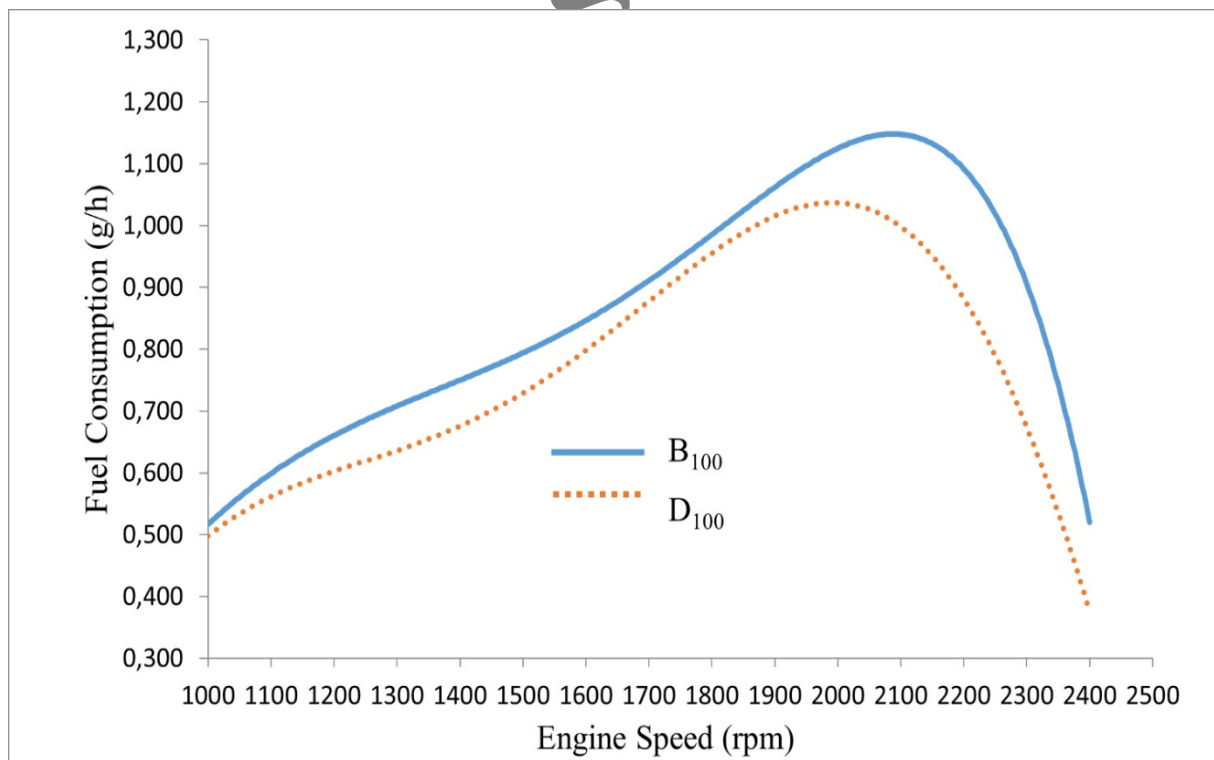


Figure 4. Fuel consumption values depending on engine speed

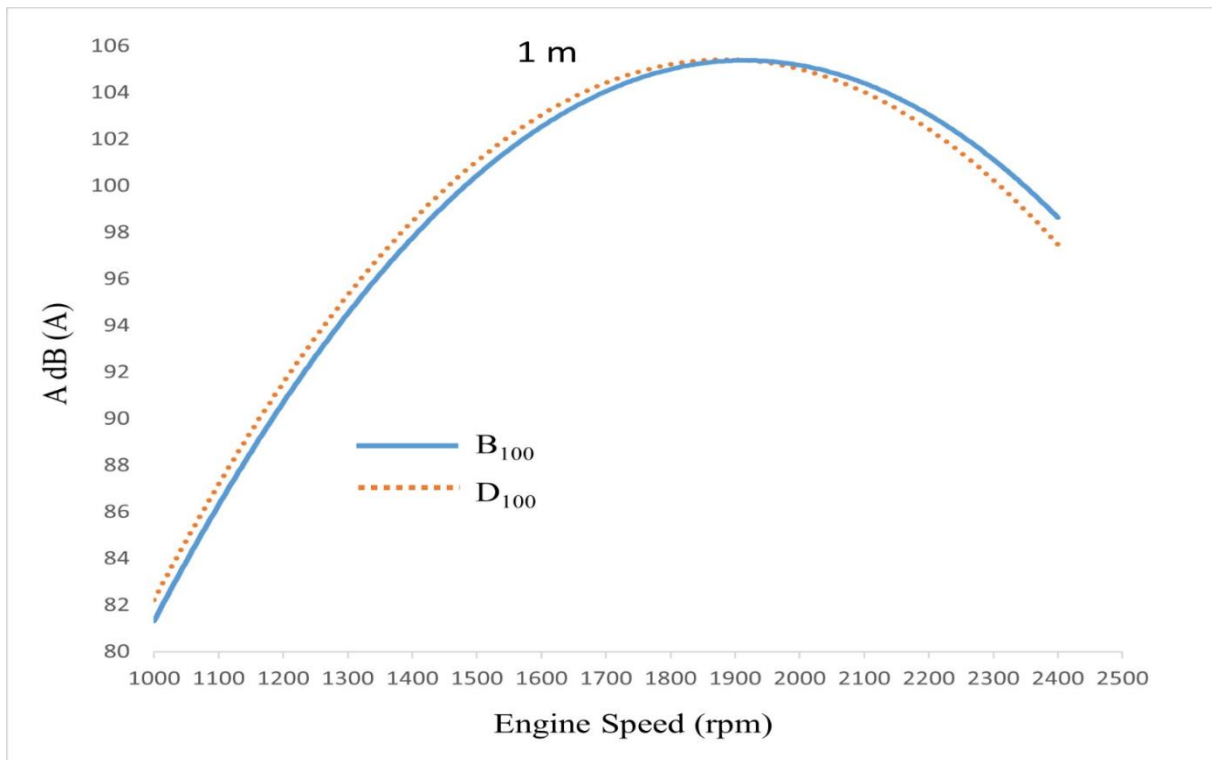


Figure 5. Noise emissions of fuel at 1 meter from point A depending on engine speed

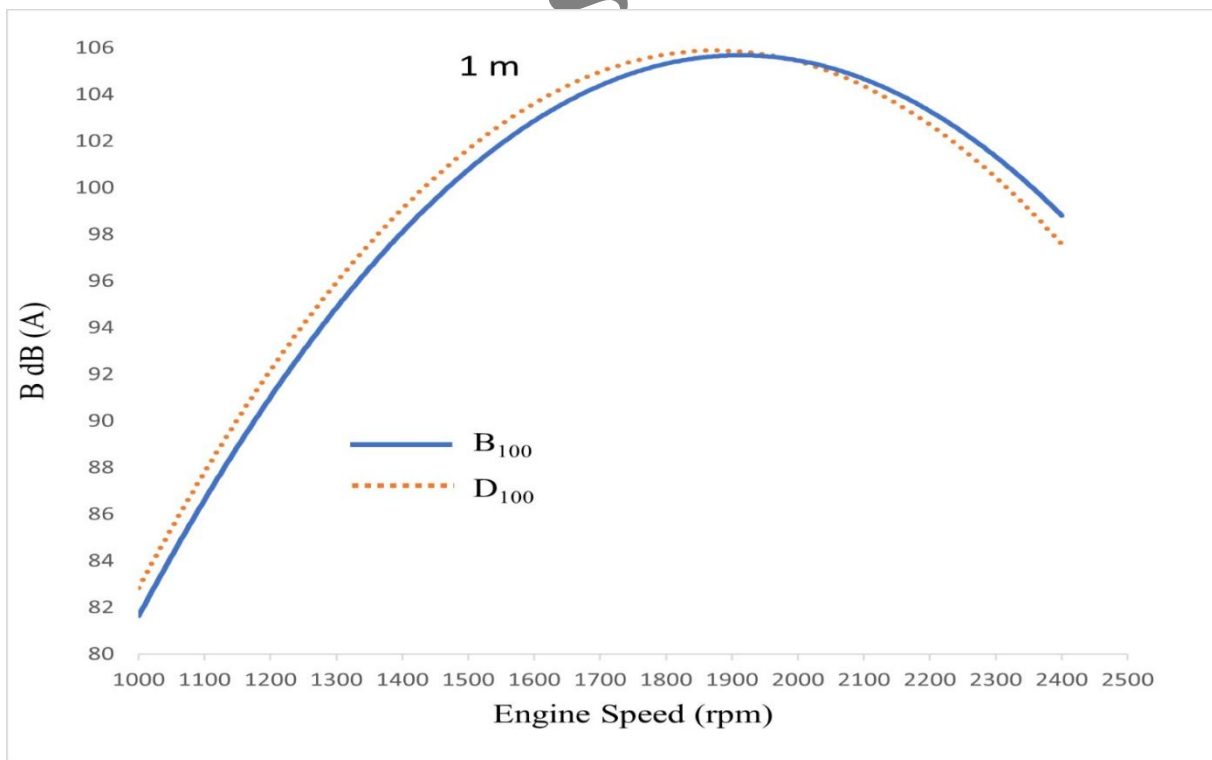


Figure 6. Noise emissions of fuel at 1 meter from point B depending on engine speed

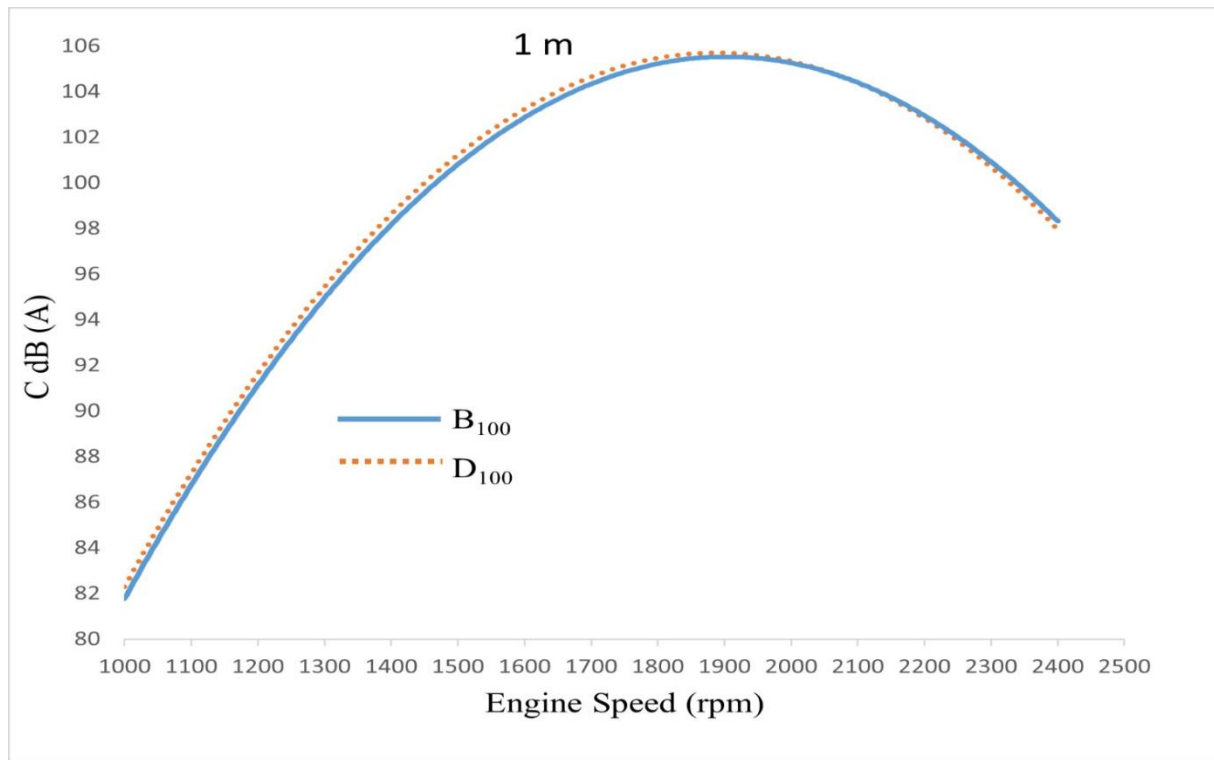


Figure 7. Noise emissions of fuel at 1 meter from point C depending on engine speed

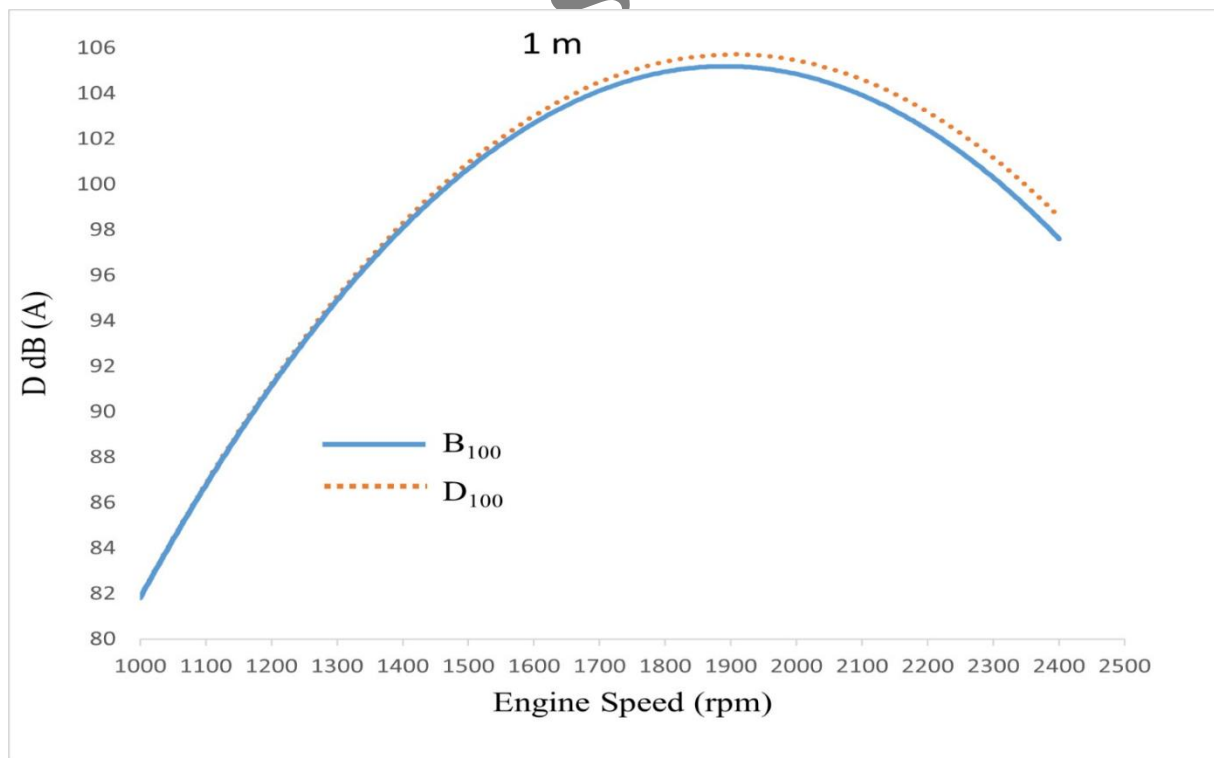


Figure 8. Noise emissions of fuel at 1 meter from point D depending on engine speed



Figure 9. Energy Analysis (HP) 1200 d/d

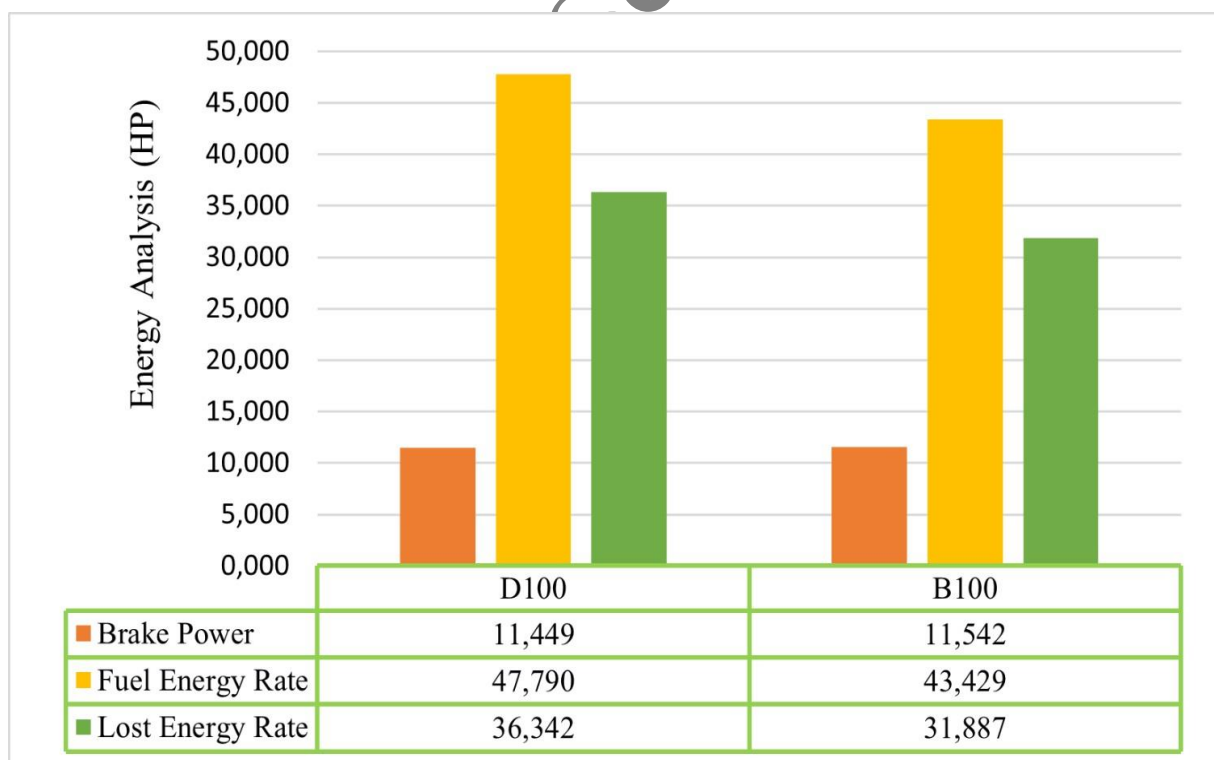


Figure 10. Energy Analysis (HP) 1500 d/d



Figure 11. Energy Analysis (HP) 2000 d/d

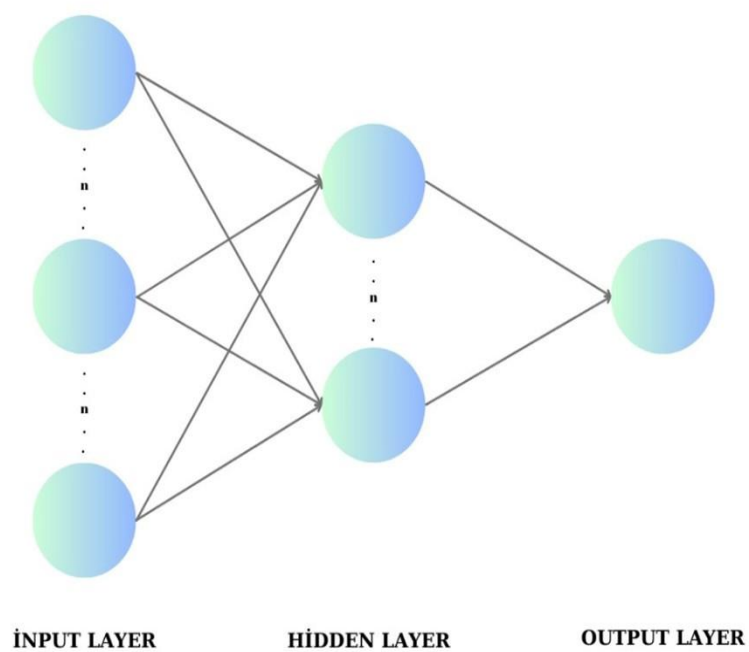


Figure 12. Network Architecture as ANN Type

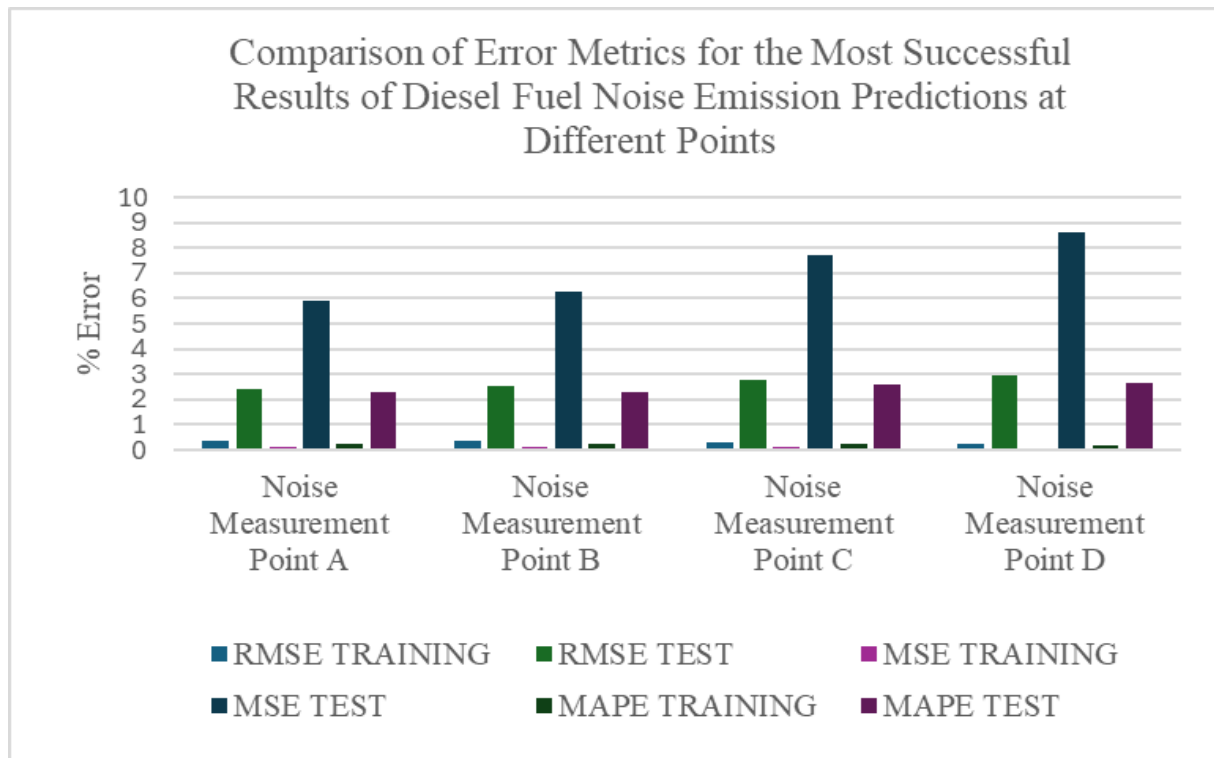


Figure 13. Comparison of error metrics for the most successful results of diesel fuel noise emission predictions at different points (D_{100})

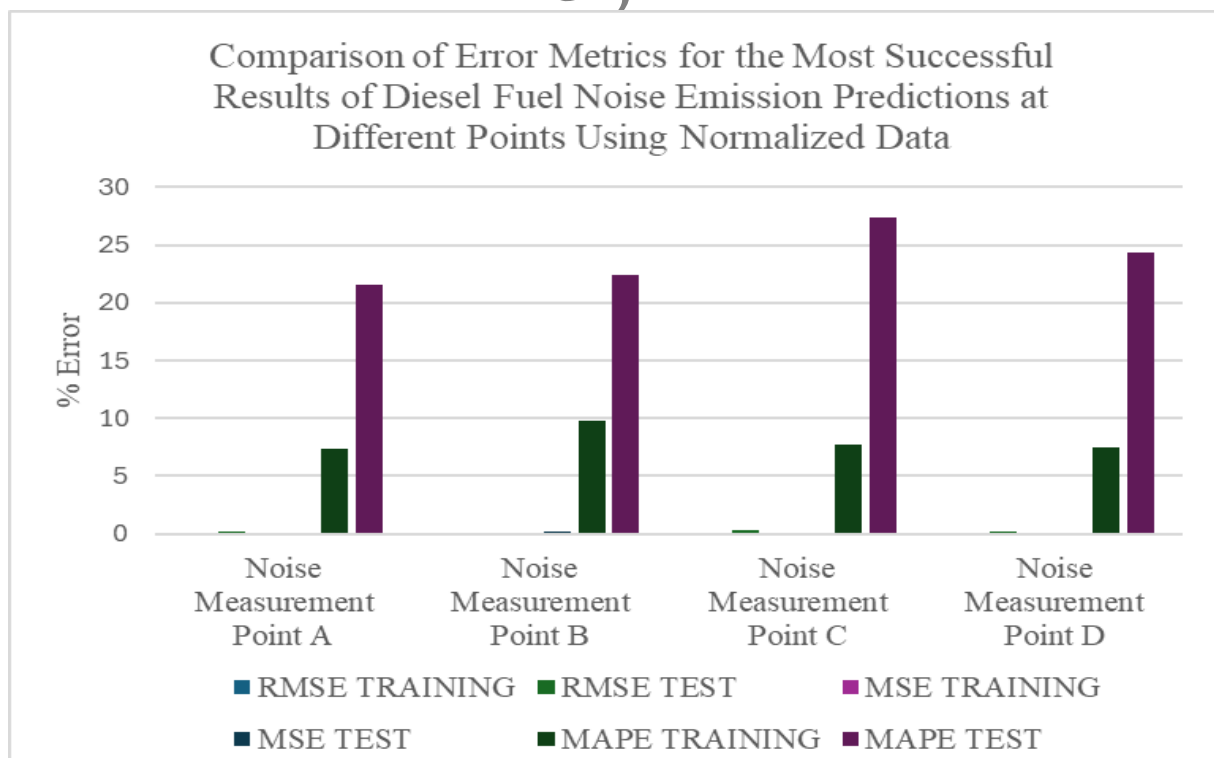


Figure 14. Comparison of error metrics for the most successful results of diesel fuel noise emission predictions at different points using normalized data (ND_{100})

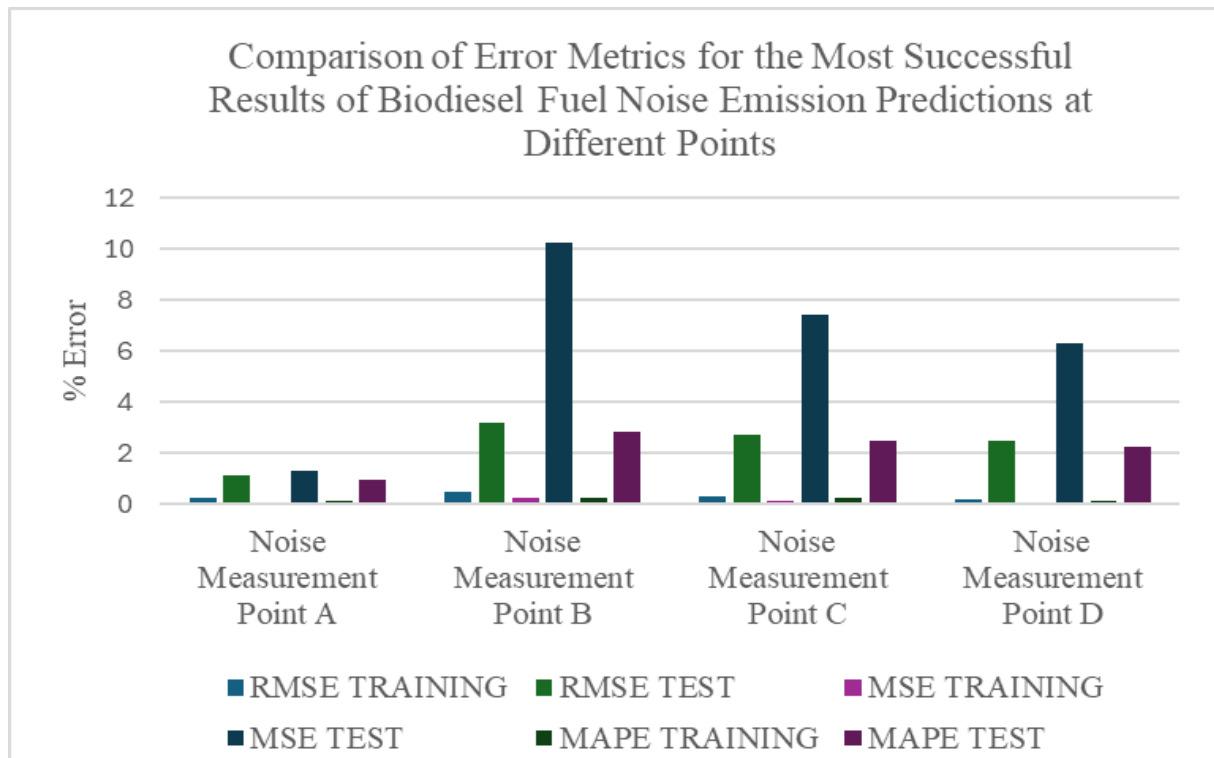


Figure 15. Comparison of error metrics for the most successful results of biodiesel fuel noise emission predictions at different points (B_{100})

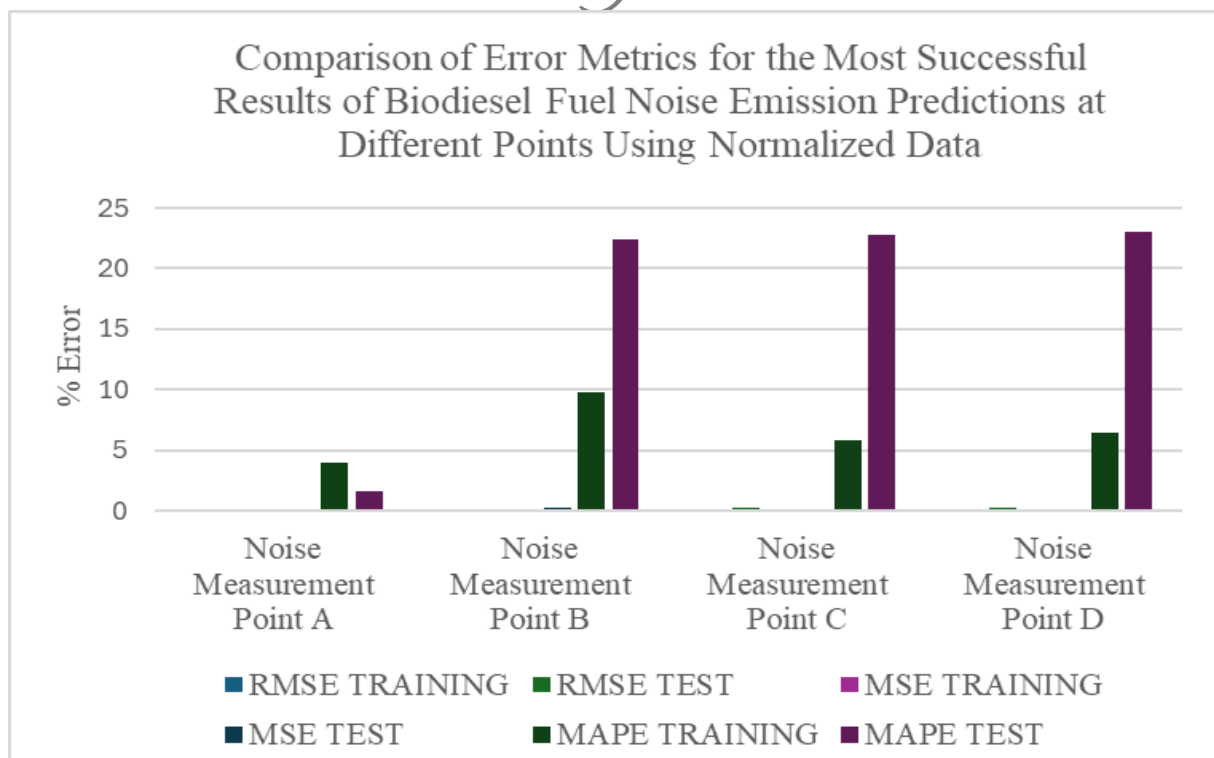


Figure 16. Comparison of error metrics for the most successful results of biodiesel fuel noise emission predictions at different points using normalized data (NB)

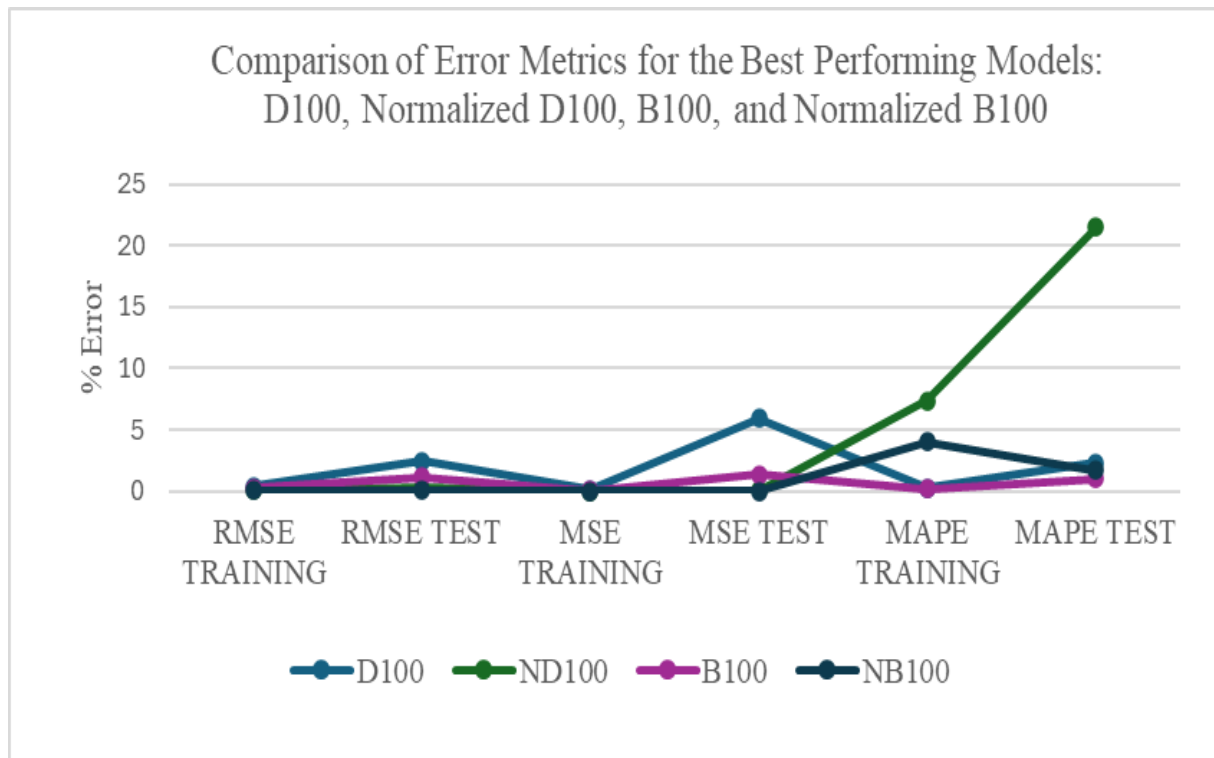


Figure 17. Comparison of error metrics for the best performing models: D₁₀₀. Normalized D₁₀₀. B₁₀₀. and normalized B₁₀₀

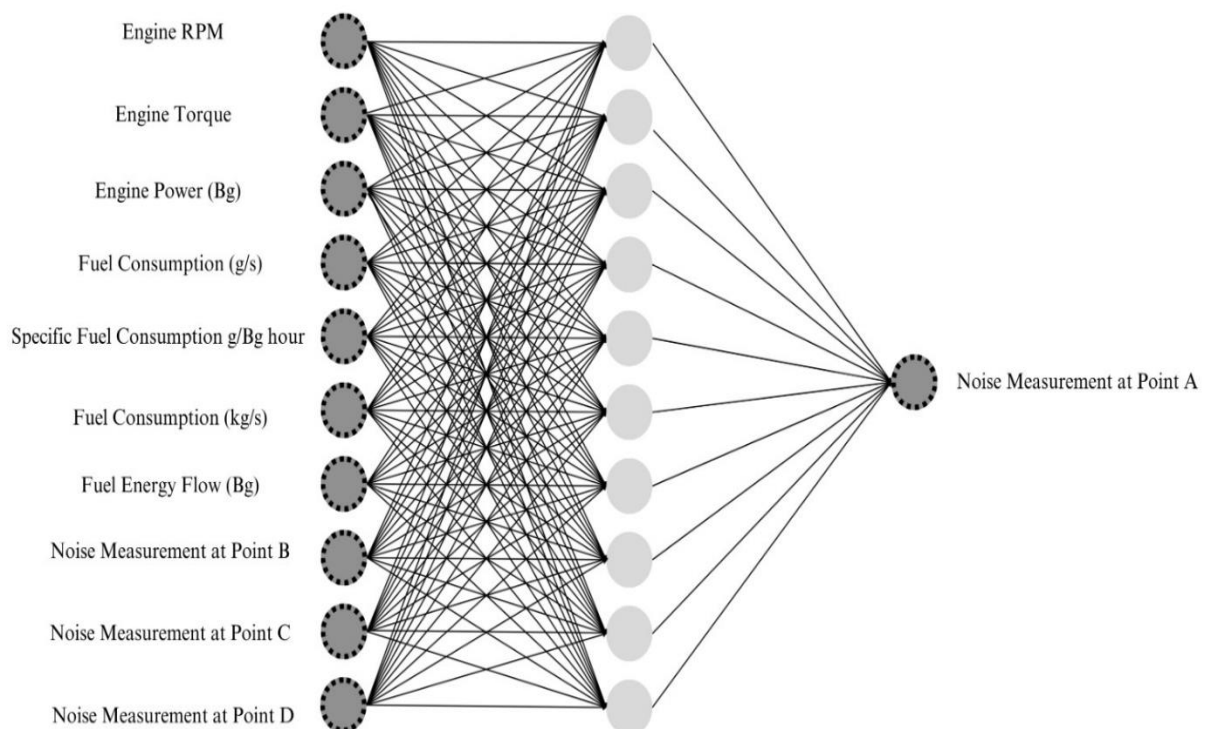


Figure 18. The most successful modeling (B₁₀₀-A Point) artificial neural networks architecture