



# Predicting Effective Efficiency of the Engine for Environmental Sustainability: A Neural Network Approach

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## ABSTRACT

Predicting engine efficiency for environmental sustainability is crucial in the automotive industry. Accurate estimation and optimization of engine efficiency aid in vehicle design decisions, fuel efficiency enhancement, and emission reduction. Traditional methods for predicting efficiency are challenging and time-consuming, leading to the adoption of artificial intelligence techniques like artificial neural networks (ANN). Neural networks can learn from complex datasets and model intricate relationships, making them promise for accurate predictions. By analyzing engine parameters such as fuel type, air-fuel ratio, speed, load, and temperature, neural networks can identify patterns influencing emission levels. These models enable engineers to optimize efficiency and reduce harmful emissions. ANN offers advantages in predicting efficiency by learning from vast amounts of data, extracting meaningful patterns, and identifying complex relationships. Accurate predictions result in better performance, fuel economy, and reduced environmental impacts. Studies have successfully employed ANN to estimate engine emissions and performance, showcasing its reliability in predicting engine characteristics. By leveraging ANN, informed decisions can be made regarding engine design, adjustments, and optimization techniques, leading to enhanced fuel efficiency and reduced emissions. Predicting engine efficiency using ANN holds promise for achieving environmental sustainability in the automotive sector.

**Keywords:** Engine efficiency prediction, Environmental sustainability, Artificial neural networks (ANN), Emission reduction, Fuel efficiency enhancement

## 1. Introduction

Predicting the effective efficiency of engines for environmental sustainability has become a crucial area of research and development in the automotive industry. The accurate estimation and optimization of the effective efficiency of engines play a significant role in making informed decisions for vehicle design and adjustments, enhancing fuel efficiency, and reducing emissions. The automotive industry is constantly seeking innovations and improvements due to the impact of rapidly advancing technologies. In this process, accurately predicting and optimizing automobile efficiency is crucial. Accurately evaluating effective efficiency can aid in making better engine design and adjustment decisions, increasing fuel efficiency, and reducing emissions. Predicting effective efficiency is critical for the automotive industry to reduce costs and offer more competitive and innovative products. Accurate predictions result in better performance, fuel economy, and driving experience while reducing environmental impacts. Therefore, predicting effective efficiency plays a significant role in the automotive sector's research and development efforts and decision-making processes.

Predicting automobile effective efficiency using traditional methods can be challenging and often time-consuming. As a result, artificial intelligence techniques, particularly artificial neural networks (ANN), have become an attractive research topic in this field. ANN are powerful learning algorithms capable of learning from complex datasets and modeling complex relationships. Therefore, using ANN to predict automobile effective efficiency holds promise for achieving more accurate and effective results. Emissions from internal combustion engines, such as vehicles, contribute significantly to air pollution and adversely affect the environment and human health. Neural networks provide a powerful tool for modeling and predicting



engine emissions accurately. Neural networks can learn complex patterns and relationships from large datasets, making them well-suited for predicting emissions. By analyzing various engine parameters, such as fuel type, air-fuel ratio, engine speed, load, and temperature, neural networks can identify correlations and patterns influencing emission levels. These models can then estimate emissions based on input parameters, enabling engineers to optimize effective efficiency and reduce harmful pollutant releases. By utilizing a neural network approach, the prediction of effective efficiency can be effectively carried out, leading to more environmentally friendly outcomes. ANN offer several advantages in predicting effective efficiency from an environmental sustainability perspective. These models can learn from vast amounts of data, extract meaningful patterns, and identify complex relationships. By accurately predicting effective efficiency, decision-makers can make informed choices regarding engine design, adjustments, and optimization techniques. This leads to enhanced fuel efficiency, reduced emissions, and improved environmental impact.

Uslu and Celik [1] utilized ANN to estimate the operational efficiency and emissions of a single-cylinder, direct-injection, air-cooled diesel engine using fuel mixtures of diethyl ether (DEE) and diesel. The ANN model accurately predicted the engine's performance and emissions, achieving regression coefficients ( $R^2$ ) ranging from 0.964 to 0.9878. The mean relative error (MRE) values also ranged from 0.51% to 4.8%. Fu et al. [2] aimed to evaluate the effectiveness of a statistical modeling approach employing ANN in predicting the efficiency and emissions of a calibrated spark ignition (SI) engine. The ANN algorithm utilized engine speed and load as input variables, while fuel consumption and emissions were the output variables. The results demonstrated that the well-trained network accurately forecasted engine efficiency, unburned hydrocarbons, carbon monoxide, and nitrogen oxide emissions with minimal errors and a high coefficient of determination. Another study focused on using an ANN to predict diesel engine performance using biodiesel, bioethanol, and biogas. The researchers developed the ANN model to overcome the challenges and costs associated with traditional engine experiments. The ANN incorporated fuel mixtures with varying percentages of biofuels, and experimental tests were conducted to collect reference values. The estimated values from the ANN model were compared with the experimental results, demonstrating the model's reliability in estimating engine performance. Statistical analyses indicated a reliability value of 99.94% for the ANN model, supporting its effectiveness in predicting engine performance [3]. Another study focused on applying ANN modeling to predict engine performance parameters, specifically brake-specific fuel consumption, effective power, average effective pressure, and exhaust gas temperature, for a methanol engine. Experimental data from tests conducted on a four-cylinder, four-stroke engine at various speeds and torques were used to train the ANN model using a backpropagation algorithm. The accuracy of the ANN predictions was evaluated by comparing them with the experimental results, revealing high  $R^2$  values close to 1, small RMS values, and mean errors. This demonstrated that the developed ANN model effectively predicted engine performance parameters for internal combustion engines [4]. The article focused on using ANN to model a diesel engine fueled with waste-cooking biodiesel to predict engine performance parameters and exhaust emissions. Experimental data from tests conducted on a two-cylinder, four-stroke diesel engine operating at different speeds using blends of waste vegetable cooking biodiesel and diesel fuel were used to train the ANN model. The study found that the ANN model effectively predicted engine performance and exhaust emissions, with high correlation coefficients and low mean square error values. The results indicated that blends of waste vegetable oil methyl ester with diesel fuel improved engine performance and emission characteristics [5].

In conclusion, the prediction of the effective efficiency of the engine using a neural network approach is a promising method for achieving environmental sustainability in the automotive industry [6], [7]. By leveraging the capabilities of ANN, accurate predictions can be made, enabling better decision-making processes, and contributing to the development of eco-friendly vehicles [8]–[10]. This approach can potentially drive positive change by optimizing effective efficiency for reducing environmental impact and promoting a sustainable future. This research aims to predict the effective efficiency of the engine using ANN for the purpose of environmental sustainability. Utilizing ANN to forecast the efficiency, emissions, and other performance characteristics of engines can assist in developing strategies to reduce environmental impacts. This study aims to explore the potential of ANN to provide insights into engine technologies' sustainability and environmental effects.

## 2. Material and Methods

### 2.1. Artificial Neural Networks (ANN)

Artificial neural networks, also known as ANN or neural networks, are artificial models designed for computer systems to solve complex problems. Inspired by the functioning principles of the human brain, ANN can recognize patterns in large datasets, analyze complex relationships, and make predictions. Neural networks comprise neurons (nerve cells) and the network structure where these neurons communicate. Figure 1 depicts the structure of a basic artificial neuron.

ANN is constructed by linking artificial neural cells together, forming intricate structures. This network stands out with its layered structure while processing input data. It generally consists of three fundamental layers: the input, hidden, and output. Figure 2 shows the basic structure of an ANN. The input layer receives data from the external world and initiates the processing by transmitting it to the neurons. Each input neuron represents different features of the data. Hidden layers identify learned patterns from input data and extract features. Each hidden layer receives outputs from the neurons in the previous layer and continues the process by transmitting them to its neurons. The output layer utilizes the information from the hidden

layers to generate results or make decisions regarding a specific output. The complexity of the problem determines the variation in the number of hidden layers and neurons within an ANN [12], [13].

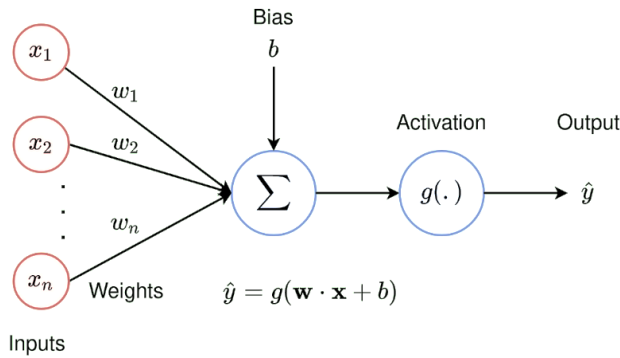


Figure 1 A basic structure of an artificial neuron [11]

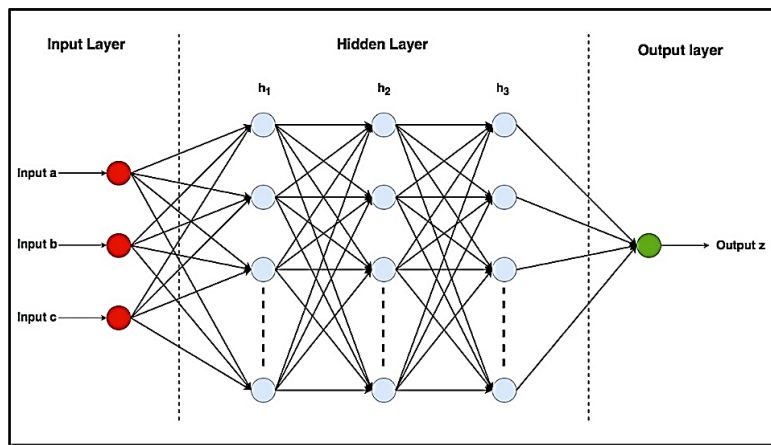


Figure 2 The basic structure of an ANN [14]

ANN employ activation functions to perform computations within neurons. Activation functions take the total input of each neuron and produce an output value. These functions possess non-linear characteristics that enhance the decision-making ability of the neural network. Common activation functions include sigmoid, ReLU (Rectified Linear Unit), and tanh (hyperbolic tangent) [15]. During the training of ANN, datasets are utilized, and parameters such as weights and biases are adjusted to improve the network's performance. This process is typically accomplished using the backpropagation algorithm. Backpropagation involves calculating the error by comparing the network's predictions with the actual results and then propagating these errors backward to update the weights.

The steps of the ANN modeling methodology are explained in Figure 3:

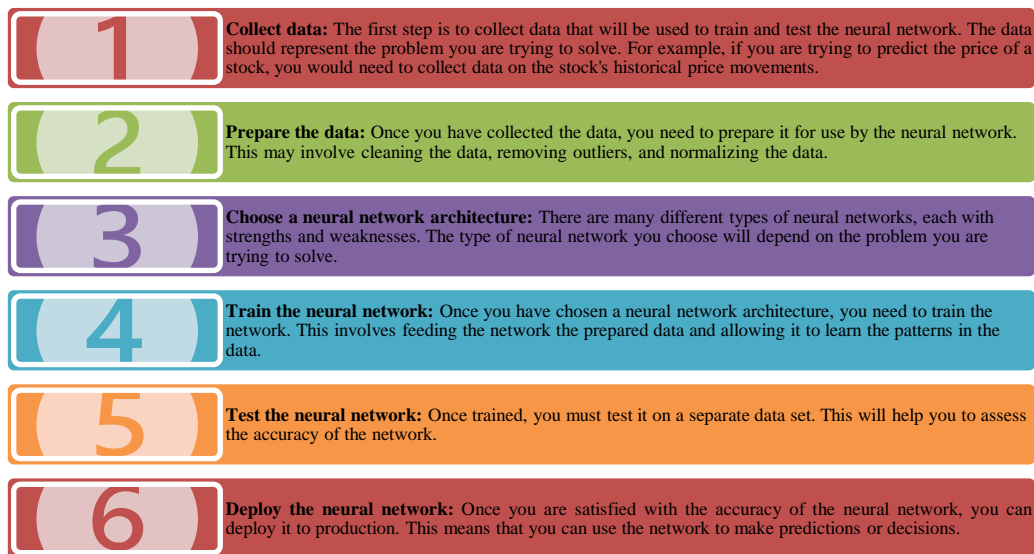


Figure 3 The Steps Involved in ANN Modeling Methodology

## 2.2. Dataset

The dataset used in this study was collected through experiments. The experiments were conducted to determine the performance of the engine. The engine was tested under different conditions, including different types of engines (standard, e10, e20), fuel ratios (gasoline and ethanol), speeds (rpm), torques (Nm), effective powers (kW), and specific fuel consumptions (g/kWh) to determine effective efficiency (%). The values of effective efficiency (%) were obtained from the experiments. The dataset consists of 90 rows of data. Statistical information regarding the dataset is provided in Table 1.

Table 1 Statistical information related to the dataset utilized in this study

| Features |                            | Unit     | Minimum | Maximum | Average | Explanation        |
|----------|----------------------------|----------|---------|---------|---------|--------------------|
|          | Engine Types               | -        | -       | -       | -       | Standard, e10, e20 |
| Input    | Fuel Ratio                 | Gasoline | 0.8     | 1       | 0.9     |                    |
|          |                            | Ethanol  | 0       | 0.2     | 0.1     |                    |
|          | Engine Speeds              | rpm      | 1400    | 3400    | 2400    |                    |
|          | Torque                     | Nm       | 29.27   | 34.95   | 31.74   |                    |
|          | Effective Power            | kW       | 4.21    | 11.46   | 7.98    |                    |
|          | Specific Fuel Consumptions | g/kWh    | 270.47  | 348.66  | 303.34  |                    |
| Output   |                            | %        | 24.28   | 31.12   | 28.06   |                    |

## 2.3. Data Normalization

Data normalization is a process of scaling the values of the data so that they fall within a specific range. This is often done to improve the performance of machine learning algorithms, such as ANNs. Normalizing the data allows us to mitigate the influence of redundant data repetition and confine the data within a range compatible with ANNs. This normalization process enhances the accuracy and efficiency of the ANN model, resulting in improved performance. In this study, the data is normalized using the min-max normalization method described in Equation 1 [16].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} (u - l) + l \quad (1)$$

where:

- $x$  is the original data.
- $x'$  is the normalized data.
- $x_{max}, x_{min}$  are the original vector's maximum and minimum values.
- $u, l$  are respectively the upper and lower values of the new range for normalized data.

## 3. Results and Discussion

The dataset utilized in this study was obtained through experiments to evaluate the engine's effective efficiency. The dataset consists of one dependent variable and seven independent variables. An overview of the dataset is provided in Table 1. In total, there are 90 rows of data. After applying min-max normalization using Equation 1, the dataset was randomly split into training (75%, 62 data), validation (15%, 14 data), and testing (15%, 14 data) sets.

To find the best number of neurons in the hidden layer, a single-hidden-layer ANN architecture was constructed. The number of neurons in the hidden layer was systematically varied from 5 to 50 in increments of 5. The network was trained using the Levenberg-Marquardt algorithm as the learning algorithm. The hidden layer utilized the sigmoid activation function, while the output layer employed the pureline function. During training, a set of input-output pairs was presented, where the inputs represented engine parameters and the outputs represented corresponding emission levels. Through backpropagation, the network adjusted its internal weights and biases to minimize the difference between predicted and actual emission values. Once trained, the neural network demonstrated accurate predictions for unseen input data. The network's performance was evaluated using the mean square error (MSE) index, and the results indicated that the optimal number of neurons in the hidden layer for predicting engine performance was determined to be 10, as depicted in Figure 4.

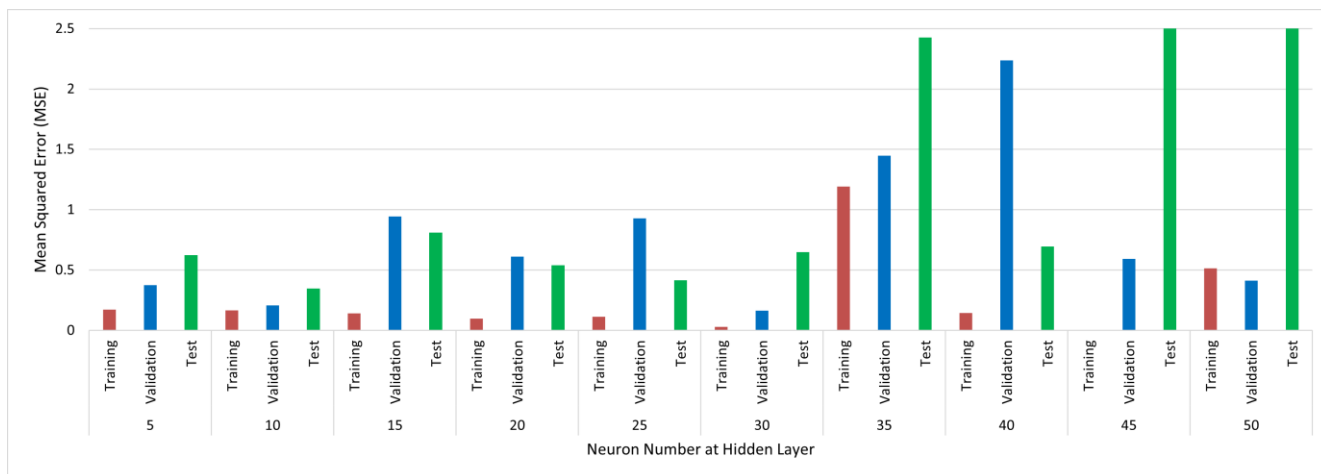


Figure 4 Determination of Neuron Number at the Hidden Layer

In Figure 5, an ANN structure consists of seven independent variables and one dependent variable, with a hidden layer containing 10 neurons. The proposed ANN model is illustrated in Figure 6.

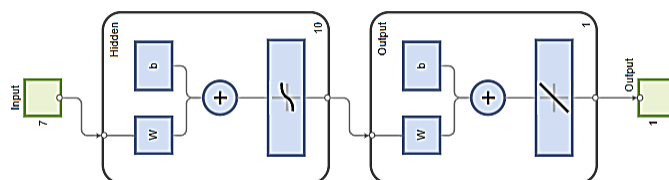


Figure 5 ANN Architecture Utilized for Prediction of the Effective Efficiency of the Engine

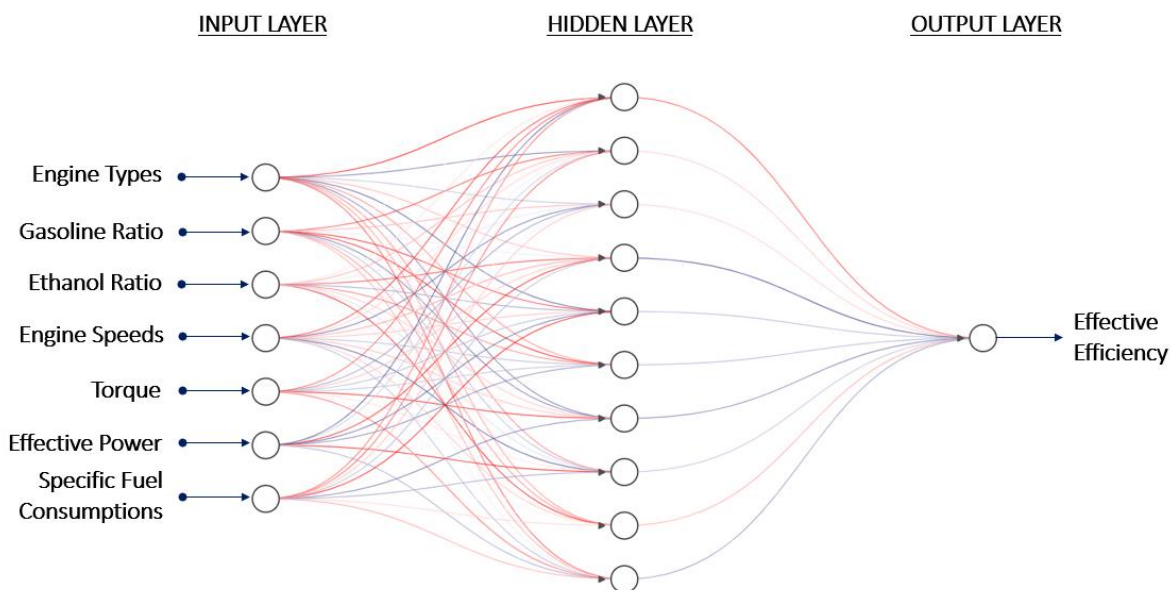


Figure 6 The Proposed ANN Model.

Table 2 Training Progress of the Network

| Unit              | Initial Value | Stopped Value | Target Value |
|-------------------|---------------|---------------|--------------|
| Epoch             | 0             | 13            | 1000         |
| Elapsed Time      | -             | 00:00:00      | -            |
| Performance       | 27.1          | 0.101         | 0            |
| Gradient          | 54.9          | 0.0638        | 1e-07        |
| Mu                | 0.001         | 0.01          | 1e+10        |
| Validation Checks | 0             | 6             | 6            |

The data about the training progress of the network is presented in Table 3. It was observed that the network exhibited significantly good performance, with a performance error of 0.101, which is closer to the target error of 0.01. The network achieved this level of performance within 13 iterations, which is considerably fewer than the initial 1000 epochs. The gradient function was calculated to be 0.0638, and the training gain (Mu) was set to 0.01. A validation check of six (6) was recorded, aligning with expectations as weight bias had been addressed through the normalization of the raw data. The Mean Squared Error (MSE) and correlation coefficient (R) values associated with the network training are displayed in Table 3. These values demonstrate that the network training has been remarkably successful, as indicated by the small MSE values and the high R values.

Table 3 The Mean Squared Error (MSE) and Correlation Coefficient (R) Values of the Neural Network

|            | Observations | %  | MSE    | R      |
|------------|--------------|----|--------|--------|
| Training   | 62           | 70 | 0.1667 | 0.9658 |
| Validation | 14           | 15 | 0.2064 | 0.9703 |
| Test       | 14           | 15 | 0.3452 | 0.9527 |

Figure 7 shows that the network completed its training in the 11th iteration, and the best validation performance was achieved in the 5th iteration. Lower mean square error is a fundamental criterion used to assess the training accuracy of a network. An error value of 0.20641 at epoch 7 is evidence of a network with a strong capacity to predict performance.

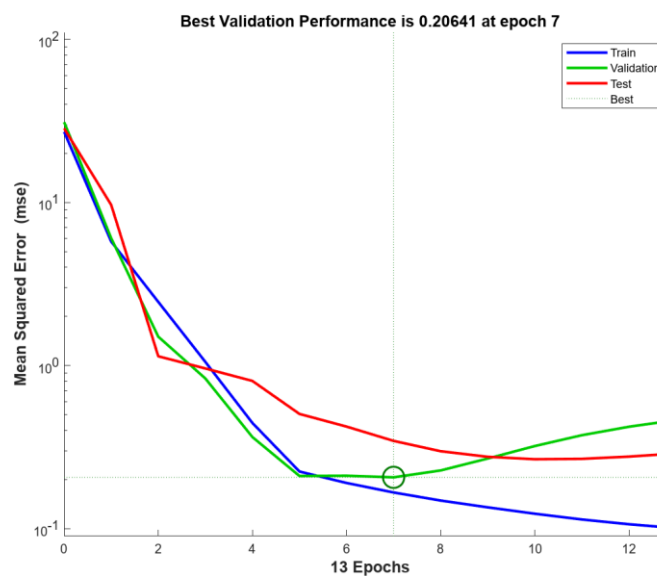


Figure 7 Error Performances for Training, Validation, and Test Data Sets

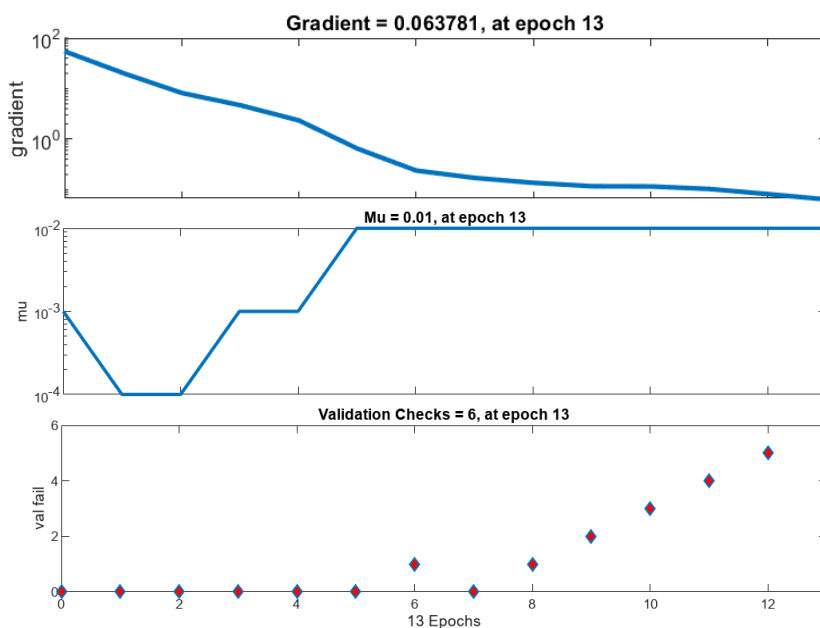
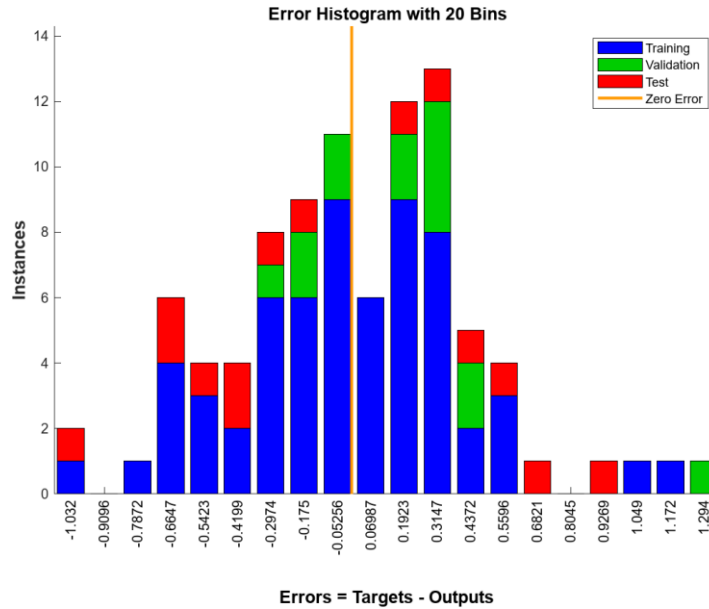


Figure 8 Training State Plot



Figure 8 illustrates the training process progress, where the gradient function depicts the change in model error during parameter updates, the momentum gain (Mu) measures the model's learning performance on the training data, and the validation check assesses the model's ability to generalize to new data. Essentially, the network calculates the loss function's gradient to assess the error contributions of the selected neurons. A lower error indicates better performance. As seen in Figure 8, the computed gradient value of 0.063781 suggests that the error contributions of the chosen neurons are minimal. A momentum gain of 0.01 reflects a high-capacity network for performance prediction.



Errors = Targets - Outputs  
Figure 9 Error Histogram Plot

The error histogram of the trained neural network for the training, validation, and testing steps is depicted in Figure 9. These error values reflect the disparities between predicted and target values and can be negative. The graph consists of vertical bars, referred to as bins, representing the number of samples falling within each bin. In this case, the total error range is divided into 20 smaller bins. The y-axis indicates the number of dataset samples within each bin. The figure demonstrates that the errors in fitting the data are reasonably distributed around zero within an acceptable range.

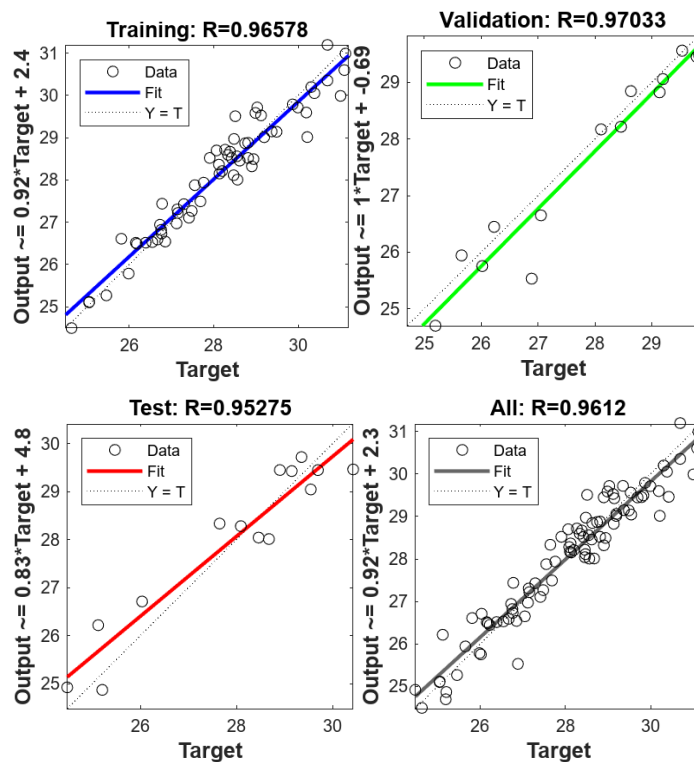


Figure 10 Regression Plot

Figure 10 displays a regression plot depicting the relationship between the input variables (types of engines (standard, e10, e20), fuel ratios (gasoline and ethanol), speeds (rpm), torques (Nm), effective powers (kW), and specific fuel consumptions (g/kWh)) and the target variable (effective efficiency of the engine (%)), alongside the training, validation, and testing progress. The calculated values of the correlation coefficient (R), observed in Figure 10, indicate that the network has been effectively trained and can be utilized for rainfall prediction.

#### 4. Conclusions

In this study, our main objective was to utilize an ANN to predict the effective efficiency of engines. We aimed to establish an appropriate ANN architecture that could accurately predict the engine's effective efficiency based on specific input parameters, including engine types (standard, e10, e20), fuel ratios (gasoline and ethanol), speeds (rpm), torques (Nm), effective powers (kW), and specific fuel consumptions (g/kWh). Accurate prediction of the effective efficiency of the engine through a neural network approach enables the optimization of engine performance, facilitates the development of eco-friendly vehicles, ensures compliance with environmental regulations, and contributes to a sustainable future.

Optimizing engine performance is achieved through accurate prediction of effective efficiency, allowing for the identification of optimal operating conditions. This optimization leads to improved fuel efficiency, reduced emissions, and minimized environmental impact. Furthermore, the study contributes to developing eco-friendly vehicles by providing insights into the factors influencing effective efficiency. This knowledge can be applied in designing and manufacturing engines that are more sustainable and energy efficient. Moreover, the accurate prediction of engine efficiency and emissions ensures compliance with strict environmental regulations imposed by governing bodies. Meeting these regulations not only avoids penalties but also actively contributes to reducing the overall environmental impact of the automotive industry.

Ultimately, the study's focus on enhancing engine efficiency and reducing emissions aligns with the broader objective of achieving environmental sustainability in the automotive sector. By prioritizing energy efficiency, reduced emissions, and environmental responsibility, a sustainable future can be realized.

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#### **Conflict of Interest Notice**

The authors declare that there is no conflict of interest regarding the publication of this paper.

#### **Ethical Approval and Informed Consent**

It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

#### **Availability of data and material**

Not applicable.

#### **Plagiarism Statement**

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