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**Research Article**

# Data Driven Automotive Engine Modelling and Calibration using Artificial Neural Network

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**ABSTRACT**

The evaluation of automobile diesel engine models equipped with BS6 technology and above is still in its early stages, making both physical testing and predictive modeling novel areas of research. This study aims to develop an Artificial Neural Network (ANN) model for predicting the performance parameters of automobile diesel engines, including brake power (BP), brake-specific fuel consumption (BSFC), brake thermal efficiency (BTE), nitrogen oxides (NOX), volumetric efficiency (VE), and exhaust gas temperature (EGT). Currently, engine modeling and calibration rely on expensive tools that require skilled manpower and licensing costs, limiting accessibility for research. Additionally, the accuracy of conventional modeling tools is typically around 60%, which can be improved to 90% through parameter optimization. Furthermore, engine modeling is a time-consuming and repetitive process across different vehicle models and variants, necessitating more efficient alternatives. To address these challenges, this research focuses on two key objectives: 1. Developing a data-driven automotive diesel engine model for Hardware-in-the-Loop (HiL) simulation using ANN. 2. Predicting engine performance and emissions under real-world drive cycles. The Feedforward Backpropagation Network is trained using the Levenberg-Marquardt algorithm to achieve optimal performance. Experimental validation shows that the trained ANN engine model accurately predicts engine emissions and performance within the provided drive cycle, demonstrating its potential as an efficient and cost-effective alternative to traditional modeling techniques.

**Keywords:** Vehicle engine modelling, Artificial Neural network, HIL simulation, Control and optimization, Neuro computing.

## INTRODUCTION

THE automotive industry has recently experienced remarkable growth [1]. The requirement for pollution control is becoming essential in the automotive industry along with the improvement in performance [2]. Every nation in the world is making the required adjustments to its emission rules in order to strike a balance between the requirement for controlled emissions and other factors [3]. As the effects of pollution throughout the world are pressuring us to regulate pollution from many industries, India leaped directly to BS VI norms from BS IV norms in order to satisfy the global emission limits [4]. The law created Bharat stage regulations to limit vehicle emissions of air pollutants. The standards put in place in 2000 concentrate on the discharge of air pollutants like particulate matter, carbon monoxide, nitrogen oxides, and Sulphur oxides (PM) [5]. As Bharat standard stages rise, there is a greater degree of parameter optimization in engine modelling. The most recent standard, known as BS-VI, can be explained in the following ways. PM and nitrogen can both be reduced by BS-VI by 80% and 70%, respectively [6]. The engine labels have been dramatically enlarged by the implementation of BS VI requirements, reaching 45000 labels [7-8].

## RELEVANCE OF THE ANN ENGINE MODEL

The standard engine modelling is unable to fully accommodate changes in the shift from BSIV to BSVI [9-10]. For the development, calibration, and testing of engine control systems in automobiles, conventionally Physics-based CAE Engine models are deployed [11]. A minor adjustment to an input parameter, however, also forces the model to complete relearning [12]. In order to prevent the re-learning of learnt weights and bias, a parameterization model is proposed [13]. The cost of the expensive modelling tools, expert labor and licensing fees required for current engine modelling and calibration restricts research. Although parameter improvement might increase modelling accuracy from the existing tools 60 to 90 percent, the process is exceedingly time-consuming and repetitious for all vehicle types and variants. The creation of these control measures necessitates the conduct of relevant research and development. The growing quantity of operational factors, in addition to their high cost and time-intensive nature, are driving Original Equipment Manufacturers (OEM) to develop new simulation techniques.

## ANN MODEL

A computer model that mimics how biological neural networks work is called an ANN model. This type of network deal with complex and nonlinear problems. Because of this, many of complex application choose ANN for the forecasting requirements. Typically, an ANN model has three parts: the input layer, some hidden layers, & then the output layer. Each part plays an important role in how the model functions. Since the weight of the network and biases are initially generated randomly, back propagation neural network (BPNN) is a popular approach for supervising training [15-16]. Numerous research contains information regarding the ANN theory for the characteristics prediction of internal combustion engine [17-25]. If the problem deals with the prediction tool for the application consisting of complex or nonlinear model, ANN is the best option [26]. Using the MATLAB NNToolbox, the model was created in line with the flowchart as shown in Fig. 1. A total of 75 percent of the datasets utilized as input from the engine test result, randomly chosen as training data and the remaining 25 percent were spent for validation. The goal of this prediction model is to decrease local minima and increase prediction accuracy. It is based on one hidden layer of the multilayered perceptron (MLP) structure. When pales in comparison to other kinds of ANN's models, MLP exhibits the most remarkable outcomes [27]. According to Fig. 1, the prediction model structure consists of six output levels, one hidden layer, and two input layers. For ANN modelling, a back propagation architecture with one hidden layer has been designed. Numerous studies are conducted in the area of neural network-based engine modeling for automobiles, wherein various combinations of biodiesels are employed to determine which is most appropriate, greener & more efficient [28-29].

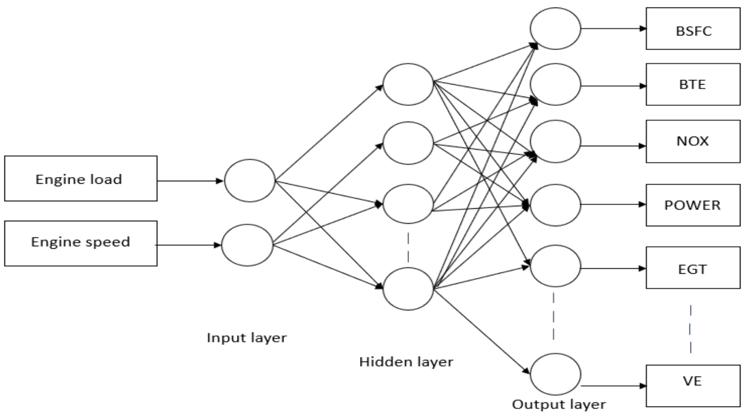


Figure 1: ANN to represent Engine modelling

One of the challenging tasks in neural network modelling is selecting the optimised network architecture. In order to avoid using a high number of weights during training, the hidden layer's number of hidden neurons was changed between 10 and 30 using a trial-and-error methodology. The values of root mean square error (RMSE) do not necessarily proportional with the number of neurons in the hidden layer, according to training findings. It has been discovered that fewer neurons would result in a decrease in network performance, whereas more neurons more than 28 will not significantly improve training results. As a result, 28 neurons were determined to be the ideal quantity for the hidden layer.

Two neurons are present in the input layer, 28 neurons are present in the hidden layer, and 6 neurons are present in the output layer in the final arrangement. Log-sigmoid and linear activation functions were chosen because they perform well in nonlinear processes, such as determining the correlation between input and output characteristics of an automobile engine. Since the Levenberg-Marquardt training algorithm offers the quickest training speed and convergence time for the backpropagation model, it has been utilised to calculate the weight and bias value[30]. To increase the prediction model's accuracy, performance goals of 1.0 x $10^{-3}$ have been set. Table 1 displays the configuration of the trained ANN model.

Table 1: ANN Model Training Configuration

| Parameter | Specification |
|---|---|
| Input layer-neurons | 2 |
| Hidden layer-neurons | 28 |
| Output layer-neuron | 6 |
| Training-function | Levenberg-Marquardt |
| Performance-function | Mean square error |
| Activation-function | Log-sigmoidal, Linear |
| Performance-goal | 1.0 x $10^{-3}$ |

To avoid complex ANN learning processes caused by high input values, all inputs and outputs are normalized between 0 and 1 for lowest and maximum values [31]. The criteria of $RMSE$, mean absolute prediction error ($MAPE$) and coefficient of determinations ($R^2$) and are used to gage the accuracy and quality of the prediction model. The RMSE shows the average discrepancy between the experiment results and the forecasts. $R^2$ on the other hand, gauges how accurately the regression depicts the actual dataset [32]. $R^2$ ranges from 0 to 1, with an ideal ANN prediction model having an $R^2$ closer to 1. The MAPE parameter displays the error in the prediction.

## ENGINE MODELLING AND RESULTS

The Levenberg-Marquardt approach was exploited to train an ANN model for predicting the performance of automotive diesel engines. The developed ANN model's ideal architecture is 2-28-6. The $R^2$and $MAPE$ criteria have been chosen to assess network accuracy. To examine the network's reaction more thoroughly, regression analysis was done between the target and related network output. The results show that the model can accurately predict the performance of car diesel engines at different engine speeds and loads. Fig 3 and Fig 4 show the correlation between ANN model predictions and experimental data w.r.t engine performance indices. There is a substantial connection between the model and the experimental data, as indicated by the increased value of $R^2$, which is almost equal to unity.

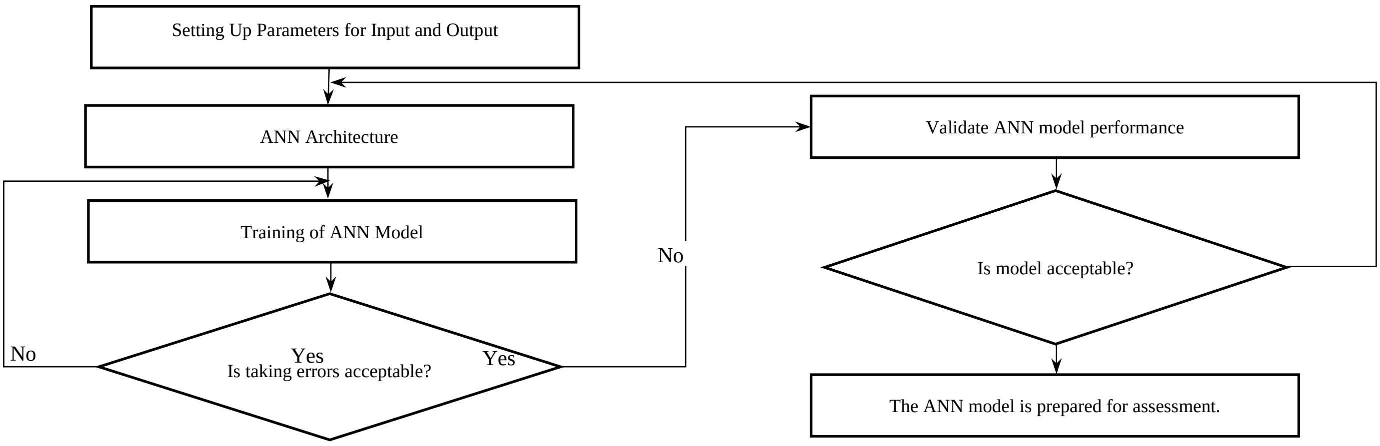


Figure 2: ANN Model flowchart

The coefficient of determinations $R^2$for the ANN prediction for (a) Brake specific fuel consumption BSFC, (b) Brake power BP, (c) Brake thermal efficiency BTE, (d) Volumetric efficiency VE, (e) Exhaust gas temperature EGT, and (f) Oxides of Nitrogen are 0.99994, 1, 0.99792, 0.99998, 0.93946 and 0.67582 respectively as shown in Fig.3 and

Fig.4. Thus, it can be said that the findings acquired using the ANN model are superior and more precise than those obtained using traditional mathematical methods. In Fig.3 and 4, the vertical axis shows the actual regression data, and the horizontal axis represents the target value. The circles illustrate the coordinates of each $R^2$ value. The continuous line represents the alignment with the training data. Training efficiency is determined by the proximity of the output to the desired target and forms a cluster along the solid line. In overall training BSFC training can be considered remarkable compared to $NO_x$. For the provided training inputs $NO_x$ training performed its best.

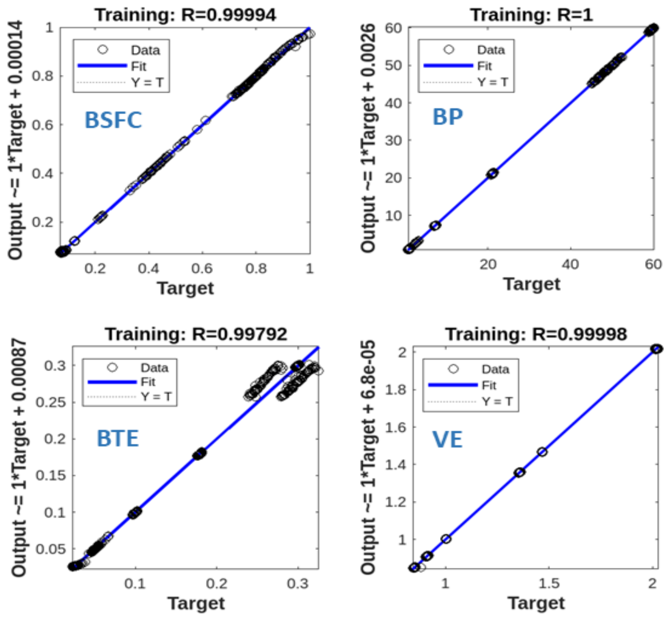


Figure 3: Trained Regression plot for BSFC, BP, BTE and VE

In Fig.3 VE and BP have a clean solid line illustrating the overlapping of $R^2$ values. In Fig.4 EGT and $NO_x$ data is scattered because of the non-linearity of the training data.

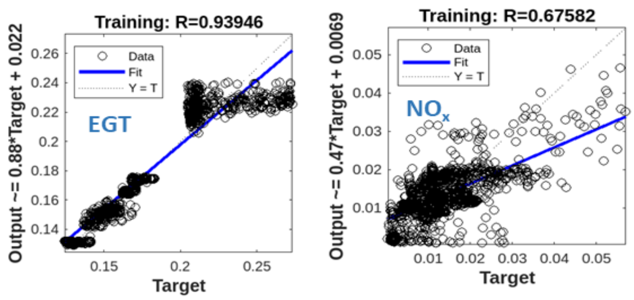


Figure 4: Trained Regression plot for EGT and NOx

In addition, the complicated and non-linear interactions between process factors and engine performance make it particularly challenging to create a relationship between them using mathematical models. The ANN prediction generates a superior prediction of the performance of the automotive diesel engine and offers the best fit to the experimental results. The diagrams presented in Figures 5 through 10 illustrate the mean square error (MSE) encountered during the network's training process. The blue graph specifically depicts the training MSE of the network.

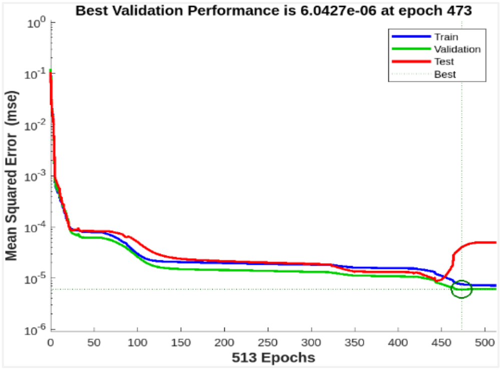


Figure 5: Performance- BSFC

The green graph shows the validation MSE of the network. The red graph shows the test MSE obtained. The BSFC network iterated for 513 epochs where the best validation performance is obtained at 473rd epoch.

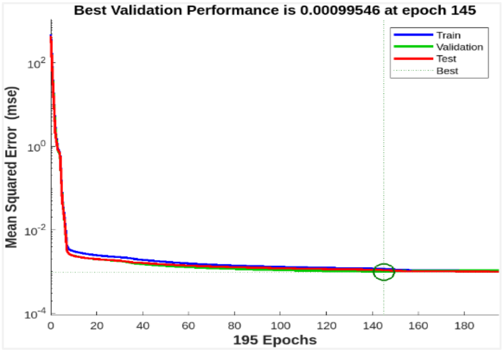


Figure 6: Performance- Brake power

The BP performance network go over 195 epochs as the best validation performance is obtained at 145th epoch.

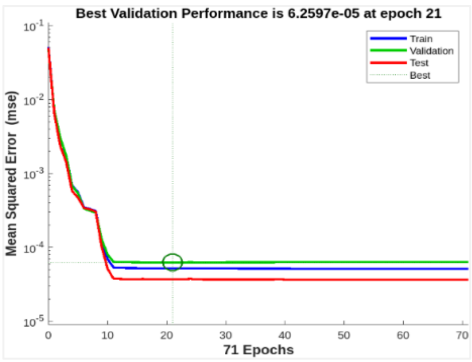


Figure 7: Performance- Brake thermal efficiency

The BTE performance network considers 71 epochs, but the best validation performance is obtained at 21st epoch.

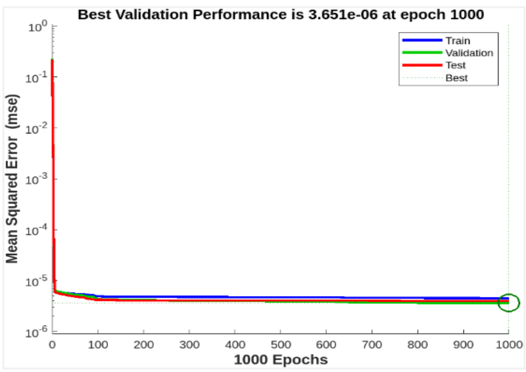


Figure 8: Performance- Volumetric efficiency

The VE training network runs 1000 epochs and attains the best validation performance at 1000th epoch.

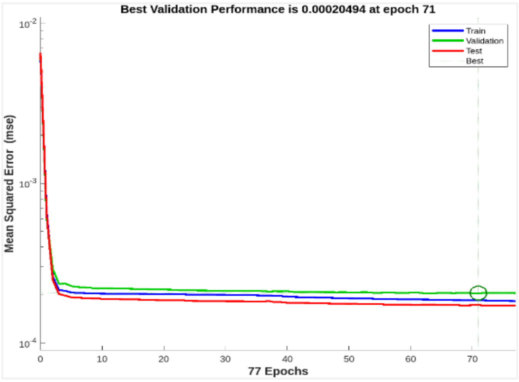


Figure 9: Performance- Exhaust gas temperature

The EGT training model totally runs 77 epochs and reaches the best validation performance at 71st epoch.

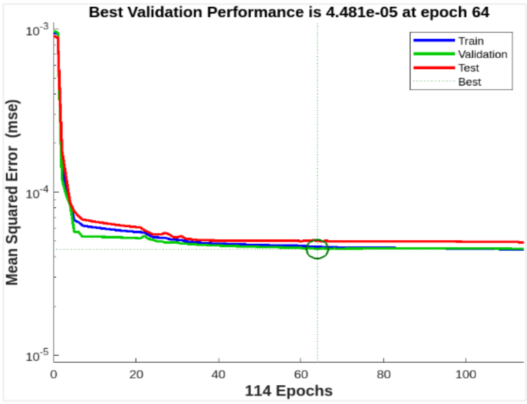


Figure 10: Performance- Oxides of nitrogen

The $NO_x$ training model totally runs 114 epochs and reaches the best validation performance at 64th epoch.

## ANN ENGINE MODELLING ON REAL TIME CYCLE

The Worldwide Harmonized Light Vehicle Test Cycles (WLTC) are chassis dynamometer examines designed to assess the fuel utilization and emissions of light-duty vehicles. These tests were developed by the UN ECE GRPE (Group of Rapporteurs on Pollution and Energy). The WLTC is a subset of the Worldwide Harmonized Light Vehicles Test Procedures (WLTP), which are documented as UNECE Global Technical Regulation No. 15 (GTR 15). The WLTP has replaced the European NEDC-based type endorsement testing process for light-duty vehicles, with the transition occurring between 2017 and 2019. The new standard aims to more accurately reflect contemporary driving conditions. To accomplish this, the WLTP extends the duration to 30 minutes, compared to the NEDC's 20 minutes, and features a more dynamic speed profile with quicker acceleration and shorter braking intervals. Additionally, the average speed has been raised to 46.5 km/h, and the maximum speed to 131.3 km/h, as illustrated in Figure 11 [33].

The mileage is 23.25 km, which is more than twice the NEDC's 11 km. In Japan, the WLTP is also utilized for vehicle certification. The cycle profile may vary based on the vehicle's top speed, defined by the original equipment manufacturer, rather than operational or safety limits. Class 3 vehicles, characterized by the highest power-to-mass ratio, are commonly used in Europe and Japan. The Typical ANN model developed with the real time data is used for predicting the outcomes with respect to WLTC class 3 cycle.

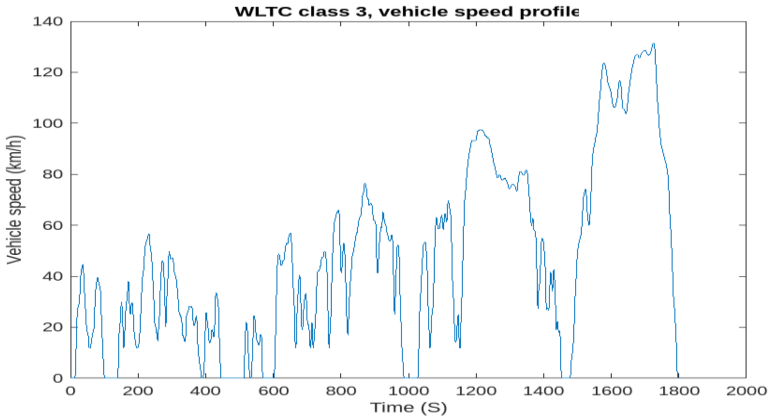


Figure 11: WLTC class 3 profile

The trained artificial neural network (ANN) engine model accurately forecasts engine performance and emissions for the specified WLTC cycle. The performance indices such as predicted BSFC, BP, BTE and VE are displayed in Fig.12, Fig.13, Fig.14 and Fig.15 respectively. Predicted Exhaust gas temperate and NOx emission are displayed in Fig.16 and Fig.17 respectively.

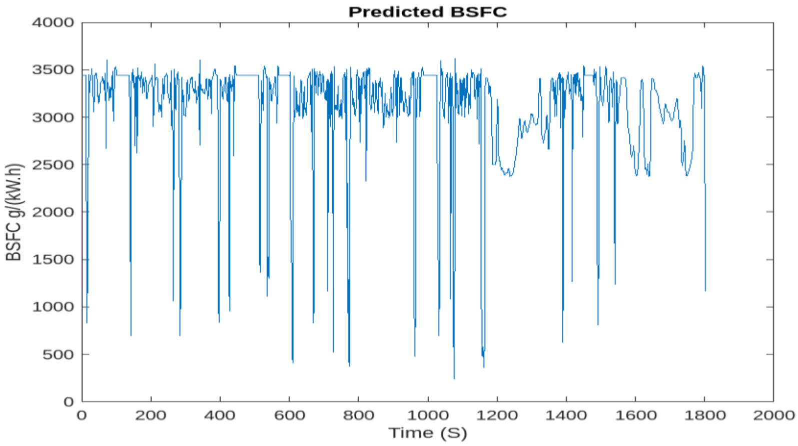


Figure 12: Predicted- BSFC

The Fig. 12 displays the graph of predicted BSFC from the given vehicle speed from WLTC drive cycle. The Graph indicates a sudden fall for the lower speed and raised to average value between 3000 and 3500 g/(kW.h), this pattern is identified due to the spontaneous acceleration. The same pattern is constant after each acceleration of the WLTC cycle.

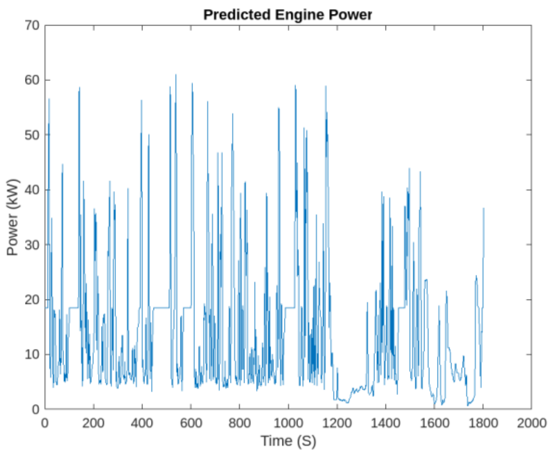


Figure 13: Predicted - Brake Power

The Fig. 13. Illustrates the graph of Predicted Brake power. According to the graph, the curve shoots to maximum when there is a rise in the vehicle speed. Engine maintains a constant BP when the vehicle is static and same is observed in the graph portraying the horizontal lines. The Brake power reduces when the vehicle cruise at higher speed with lower torque which is observed between 1200 and 1800.

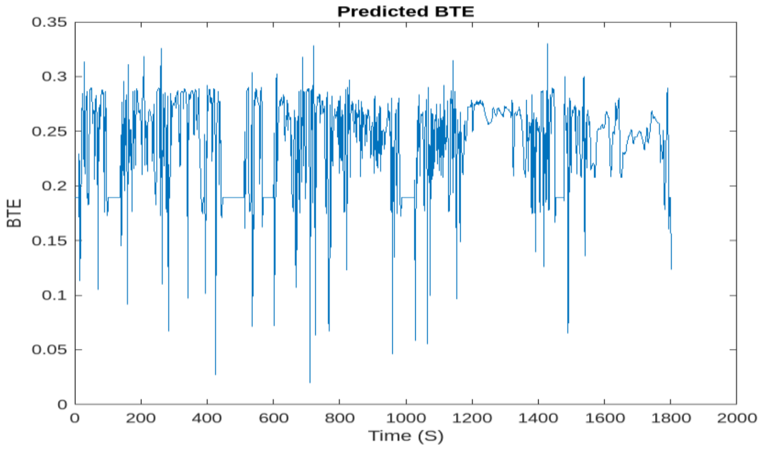


Figure 14: Predicted - Brake thermal efficiency

Fig.14 illustrates the vehicle speed (0 to 131kmph) versus variations of the BTE for diesel. The highest BTE was observed to be 33%, which was achieved at vehicle speed of 40kmph.

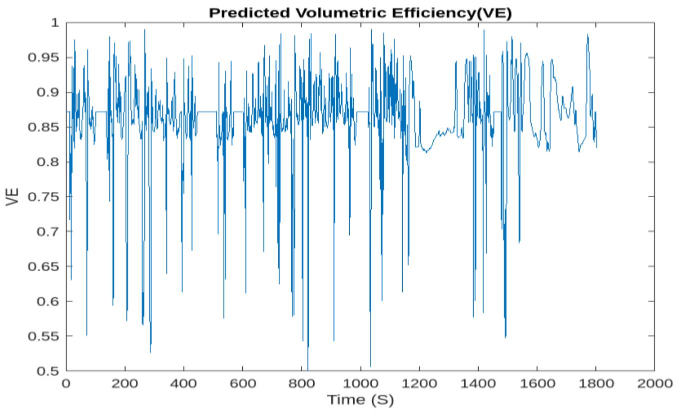


Figure 15: Predicted - Volumetric efficiency

Figure 15 illustrates the predictable trends in the volumetric efficiency (VE) behavior of the ANN engine. It was observed that VE decreases as speed increases. This reduction in vehicle speed significantly lowers fuel consumption. The volumetric efficiency rises with increasing RPM up to the point of peak torque, after which it reaches its maximum and then begins to decline.

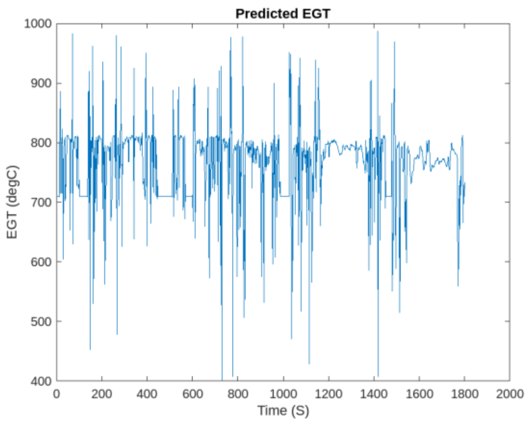


Figure 16: Predicted - Exhaust gas temperature

Figure 16 illustrates the trend of exhaust gas temperature (EGT) recorded for the ANN engine, showing that EGT values increase proportionally with engine speed. The maximum EGT was observed to peak at 990°C at a vehicle speed of 30 km/h.

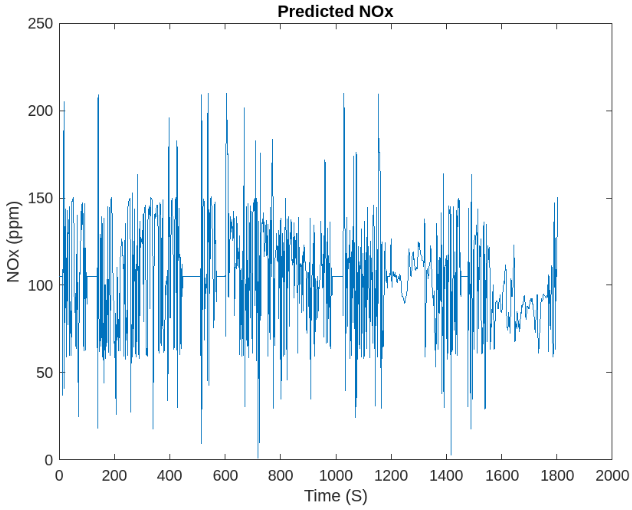


Figure 17: Predicted - Oxides of nitrogen

Figure 17 demonstrates the predictable trends in the volumetric efficiency (VE) behavior of the ANN engine. Under conditions of acceleration or high engine load, exhaust emissions increase. Specifically, NOx emissions rise with increasing speed but remain low at a stable cruising speed of approximately 130 km/h.

## CONCLUSION

For Automotive diesel engine, an ANN model has been successfully created to forecast performance. The input data is trained using the Levenberg-Marquardt technique and the ANN BP model. The mathematical model and the real experiment data have been compared to the ANN prediction findings. Following is a summary of the study's main findings.

(i) The prediction results of the ANN model, which utilized 28 neurons in the hidden layer, demonstrated a strong correlation with the experimental data.

(ii) With a coefficient of determination ($R^2$) of 0.99, the data point distribution of the ANN model closely matched the actual experimental data. In contrast, the $R^2$ for the mathematical model was slightly lower, approximately 0.85. This indicates that the developed ANN model can predict experimental data with a high degree of accuracy.

(iii) Prediction of Engine key performance and emission in a real time drive cycle such as WLTC is successful.

(iv) In non-linear issues, ANN are a highly effective strategy that are simple to apply. With dependable and endurable precision, the created ANN model may be utilized to forecast Automotive diesel engine performance and emission.

Furthermore, the scope of this work can be used to predict the performance of the biodiesel blend engine model. Another scope of this work will be used to predict the performance of engine parameters and recalibrate the input to the ECUs in the real time environment.

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