The Application of Artificial Neural Network in Prediction of the Performance of Spark Ignition Engine Running on Ethanol-Petrol Blends

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Abstract. The performance analysis of a single cylinder spark ignition engine fuelled with ethanol–petrol blends were carried out successfully at constant load conditions. E0 (Petrol), E10 (10% Ethanol, 90% Petrol), E20 (20% Ethanol, 80% Petrol) and E30 (30% Ethanol, 70% Petrol) were used as fuel. The Engine speed, mass flow rate, combustion efficiency, maximum pressure developed, brake specific fuel consumption and Exhaust gas temperature values were measured during the experiment. Using the experimental data, a Levenberg Marquardt Artificial Neural Network algorithm and Logistic sigmoid activation transfer function with a 4–10–2 model was developed to predict the brake specific fuel consumption, maximum pressure and combustion efficiency of G200 IMEX spark ignition engine using the recorded engine speed, mass flow rate, biofuels ratio and exhaust gas temperature as input variables. The performance of the Artificial Neural Network was validated by comparing the predicted data with the experimental results. The results showed that the training algorithm of Levenberg Marquardt was sufficient enough in predicting the brake specific fuel consumption, combustion pressure and combustion efficiency of the test engine. Correlation coefficient values of 0.974, 0.996 and 0.995 were obtained for brake specific fuel consumption, combustion efficiency and pressure respectively. These correlation coefficient obtained for the output parameters are very close to one (1) showing good correlation between the Artificial Neural Network predicted results and the experimental data while the Mean Square Errors were found to be very low (0.00018825 @ epoch 10 for brake specific fuel consumption, 1.0023 @ epoch 3 for combustion efficiency and 0.0013284@ epoch 5 for in-cylinder pressure). Therefore, Artificial Neural Network toolbox called up from MATLAB proved to be a useful tool for simulation of engine parameters. Artificial Neural Network model provided accurate analysis of these complex problems and has been found to be very useful for predicting the performance of the spark ignition engine. Thus, this has proved that Artificial Neural Network model could be used for predicting performance values in internal combustion engines, in this way it would be possible to conduct time and cost efficient studies instead of long experimental ones.

1. Introduction

The ever rising cost of fossil fuel internationally has forced major world economies, which are also major importers of fossil fuel, to consider renewable and cheaper alternatives to fossil fuel to compliment their energy demands. The limited nature of oil resources has made studies on alternative energy sources much more important in internal combustion engines in which oil products are used as an energy source [1–4].

The petrol engines are one of the most efficient power plants in use today; consequently, they enjoy wide application in road, rail, marine transportation and power generation. Petrol engines runs
conventionally on petrol fuels which is a fossil fuel and whose production and combustion result in the emission of gases that have adversely affected human health and environment [5]. The greenhouse gas emissions from the combustion of hydrocarbon fuels have been identified as the major causes of climate change and global warming. Climate change and global warming are serious contemporary challenges that face humanity. The numerous and varied effects of climate change on the environment, human life and the economy of the nations are becoming increasingly obvious and real.

Both the US Energy Department report of 2008 and the 2007 report of the Intergovernmental Panel on Climate Change (IPCC) associated global warming with rise in sea level, flooding, changes in rainfall pattern, deforestation, glacier retreat, increased precipitation and high hurricane power dissipation index. On human health, global warming has been linked with increase in cardiovascular diseases, asthma, and other lung diseases due to the concentration of ozone at ground level [5]. Rogers and Randolph [6] associated global warming with wide spread of diseases like dengue fever and malaria. Besides the issues of health and environment, the over dependence on fossil fuels as major sources of energy has raised the issues of energy security and incessant price increases. Fossil fuels are non-renewable and the fast depletion of their reserves could lead to their exhaustion in the near future hence a possible global energy crises may emerge.

Due to these challenges, many countries are today turning to fuels from biomass and other non-petroleum sources to substitute or supplement the conventional fuels. Alternative fuels from bio-resources are considered biodegradable, renewable and environmentally friendly [7]. Among the alternative fuels that are gaining global interest particularly for internal combustion engines are bio-fuels like Bio-ethanol and Biodiesel. While bio-ethanol is considered a good alternative fuel for petrol engines, biodiesel is considered as good alternative for diesel engines.

Bio-alcohol such as bioethanol, a colourless liquid with mild characteristic odour can be produced by fermentation of agricultural products containing sugar and starch such as wheat, sugar beet, sugar cane, corn, raffia trunk, wood and wood-like plants [8–11]. The use of bioethanol in petrol engines provides a decrease in the amount of carbon monoxide (CO) and unburned hydrocarbon in exhaust emissions [12–14]. The decrease in these emissions is related to the amount of oxygen contained in fuel blends [15].

Bio-ethanol fuel has favourable engine performances comparable to petrol fuel. Using ethanol as fuel for spark ignition engine have some advantages over petrol such as better anti-knock and emission characteristics, improved brake thermal efficiency and volumetric efficiency [16 – 19]. However, the oxygen content in ethanol reduces the heating value of the blends produced with petrol [10, 20, 21]. As a result of these qualities, increasing research attentions are being shifted to the development of bio-ethanol and biodiesel globally. Currently, edible and non-edible sugar based feedstock are under research for bio-ethanol production and some commonly used feedstock in different countries are, sugar cane in Brazil and USA, wheat and barley in Europe, palm wine, palm sap and cassava in Western Africa and maize in USA and Central Africa [22, 23].

Conducting performance experiments on engines using different operating conditions on different fuels require expenditure of considerable cost and time. At this point, artificial neural network (ANN) can be used in order to decrease cost and save time [24]. In recent years the applicability of an artificial neural network model for internal combustion engines has gained considerable success [25, 26] but skewed to diesel engines.

In a study, Uzun [27] used the ANN approach to predict air mass flow in a diesel engine. Hassan, [28] studied the prediction of diesel engine performance, emission and cylinder pressure obtained using bioethanol-biodiesel-diesel fuel blends through an artificial neural network. As a result of the study, the correlation coefficient of 0.98 was obtained between the experimental data and the predicted data. Similarly, Bekir and Selman [29] investigated the use of neural network in predicting engine torque of a biodiesel engine. The performance of the ANN was validated by comparing their predicted data with the experimental result. They observed that ANN model can predict the engine performance quite well with correlation coefficient of 0.98 obtained for engine torque. Parlak et al. [30] used ANN to predict the fuel consumption and exhaust gas temperature of
a diesel engine. Ghobadian et al. [31] also used ANN for predicting engine performance and exhaust emissions with the use of biodiesel obtained from waste oils.

However, Cay [32] showed that ANN approach could also be used for predicting performance values in a petrol engine but the available works on the use of ANN to predict performance of spark ignition engines were not elaborate with respect to the actual percentage blends of alcohol used. Puli et al. [33] looked at performance and emission prediction of a tertiary butyl alcohol gasoline blended spark ignition engine using artificial neural networks. In the study, experimental results for different load conditions with various percentages of tertiary butyl alcohol petrol blends such as 0-5% and 10% were investigated at 1500, 2000, and 2500rpm experimentally and blends of 6-9% were predicted with the ANN. Both experimental and predicted tests yielded positive results as root mean square error of about 0.9997 were obtained in the study.

Similarly, Sayin et al. [34] investigated the ANN modeling for the petrol engine to predict the brake specific fuel consumption, brake thermal efficiency, exhaust gas temperature, and exhaust gas emissions of the engine. In the study, data for training experiments were carried out using gasoline having various octane numbers (91, 93, 95 and 95.3) and operated at different engine speed and torque. Cay et al. [35] carried out study to predict the brake specific fuel consumption, effective power and exhaust gas temperature of a methane engine using ANN. Experiments were performed with a four cylinder, four stroke test engine operated at different engine speed and torques. Yusaf et al. [36] also estimated the performance and emission concentration of liquefied petroleum gas spark ignition engine using ANN.

The existing literature showed that Artificial Neural Network is a powerful modeling tool that has the ability to identify complex relationships between an input and an output data [29]. Thus, this work is geared towards developing a neural network model for predicting the brake specific fuel consumption (BSFC), combustion efficiency and maximum cylinder pressure of a single cylinder spark ignition engine in relation to its engine speeds, engine torque, mass flow rate, ethanol-petrol mixtures and exhaust gas temperature. ANN is a Meta heuristic tool that has the ability to relearn and adapt for improving its performance with the availability of updated data [29]. The model is of a great significance due to its ability to predict engine performance under varying conditions [29, 37]. For acquiring data for training, experiments were carried out using petrol-ethanol blends of various proportions at different engine speed in a single cylinder four stroke G200 IMEX engine coupled to a brake dynamometer. The exhaust of the engine is connected to a KM9106 exhaust gas analyzer. A feed forward back propagation algorithm was used for the ANN structure. The performance of the ANN is validated by comparing the predicted data with the experimental results.

This research work is justified by the current global search for alternative fuels and energy sources that are both renewable and environmentally friendly. This search has been informed by the obvious negative consequences of the over-dependence of humanity on petroleum fuels for transportation, industry, power generation etc. This work will stimulate interest in the harnessing of these abundant bio-energy resources available in the country. This has the multiplying effects of promoting agricultural activities, generation of rural employment, provision of rural infrastructures and the enhancement of the standard of living of rural dwellers. Nigeria is endowed with huge natural resources and factors deployable for bio-energy production like large arable land and favourable climate conditions. This work represents an effort to address some of these problems associated with fossil fuels by developing an alternative fuels (bio-fuels) from organic and renewable sources which will have performance characteristics similar to conventional fossil fuel. This will enlist Nigeria among the nations making frantic efforts to cut down greenhouse emissions in order to mitigate the effects of climate change.
2. Materials and Methods

2.1. Experimental Set Up and Results

The fuels used in the test include: unleaded petrol purchased from Nigerian National Petroleum Corporation (NNPC) fuel mega station at Onitsha road Owerri, Imo state Nigeria; bioethanol produced from various Nigerian feedstock through fermentation and distillation processes; blends of the produced bioethanol and petrol at various proportions [38]. The petrol, ethanol and its blends were characterized in accordance with American Society for Testing and Materials (ASTM) methods and their properties as reported by Nwufo et al. [10] are given in Table 1.

| Properties                        | Petrol | E10  | E20  | E30  | E40  | E60  | Bioethanol |
|-----------------------------------|--------|------|------|------|------|------|------------|
| Density (kg/m³)                   | 747.4  | 750.8| 760.5| 778.2| 779.2| 781.2| 789.0      |
| Vapour Pressure (kPa)             | 36     | 39   | 39   | 38   | 35.6 | 31   | 9.5        |
| Octane Number                     | RON    | 91   | 94   | 95   | 97   | 98   | 102        |
|                                  | MON    | 85   | 86   | 87.5 | 89   | 92   | 97         |
| Flash Point (°C)                  | -65.0  | -40.0| -20.0| -15.0| -13.5| -1.0 | 12.5       |
| Heating Value (MJ/kg)             | 44.4   | 44.22| 42.08| 40.48| 38.50| 35.84| 29.78      |
| Auto-Ignition Temperature (K)     | 519    | 533  | 552  | 552  | 567  | 618  | 638        |
| Stoichiometric Air/Fuel Ratio     | 15.10  | 14.12| 13.55| 12.98| 12.40| 11.25| 8.96       |

(Source: Nwufo et al. [10])

| Model                          | G200 IMEX                 |
|--------------------------------|----------------------------|
| Type                           | 4 stroke, 25° inclined single cylinder |
| Bore Stroke                    | 68mm × 45mm                |
| Engine Capacity                | 163.46cc                   |
| Piston Displacement            | 196cc                      |
| Compression Ratio              | 8.5:1                      |
| Maximum Horse Power            | 6.5 Hp/3600rpm             |
| Maximum Torque                 | 13Nm/2500rpm               |
| Fuel Consumption               | 290g/Hphr (0.389kg/kWhr)   |

Test runs were carried out on a single cylinder four stroke G200 IMEX engine coupled to a brake dynamometer. It is an air-cooled, naturally aspirated four stroke engine with the specifications shown in Table 2. The ambient temperature and pressure of the test room were measured using a thermometer and a barometer respectively. Combustion efficiency and the exhaust gas temperature were analyzed using KM9106 exhaust gas analyzer. Fuel consumption per unit time was measured using a calibrated burette and a stop watch. The specifications of the measuring devices are presented in Table 3. The schematic diagram of the experimental setup of the test engine is shown in Fig. 1.
Table 3. Technical Details of Measuring Equipment.

| Equipment          | Measurement          | Upper Limit  | Accuracy             |
|--------------------|----------------------|--------------|----------------------|
| KM9106             | O₂                   | 25.00%Vol.   | ±0.001%Vol.          |
|                    | CO                   | 10.00%Vol.   | ±0.001%Vol.          |
|                    | CO₂                  | 18.00%Vol.   | ±0.001%Vol.          |
|                    | HC                   | 10000ppm     | ±1ppmVol.            |
| Bosch RTM 430      | Smoke Capacity       | -            | ±0.1%                |
|                    | 100%                 |              |                      |
| K-type Thermocouple| Exhaust Gas          | 600°C        | ±0.1°C               |
|                    | Temperature          |              |                      |
| Barometer          | Ambient Pressure     | 4bar         | ±0.01bar             |
| Calibrated Burette | Flow Rate            | 50.10cm³     | 0.01cm³              |
|                    |                      |              |                      |
| Thermometer        | Ambient Temperature  | 100°C        | 0.1°C                |
|                    |                      |              |                      |
| Stop Watch         | Time                 | -            | 0.01sec              |

The experiments were performed at full throttle opening and at variable engine speeds (full load – constant load test) using the various ethanol petrol blends to measure the performance parameters of the engine. The engine was started and allowed to idle till the normal operating temperature was attained. The rack was adjusted to a full load position and the external load on the engine was gradually increased which resulted to changes in engine speed and torque. The engine was first run on neat petrol and then its blends. Before running the engine with a new blend of fuel, it was allowed to run for sufficient time to consume the remaining fuel from the previous experiment [38].

![Schematic Diagram of the Experimental Setup](image)

**Notes:** 1, Test bed; 2, Engine; 3, Dynamometer; 4, Carburetor; 5, Burette; 6, Gas Analyzer; 7, Digital Load Indicator. (Source: Igbokwe et al. [38])

The entire fuel samples were tested by similar procedure. Readings of engine speed, fuel consumption, exhaust gas temperature and combustion efficiency was recorded during the experiment for the various fuels.

### 2.2. Artificial Neural Networks Structure and Model

A well trained ANNs can serve as a predictive tool for solving specific problems that involves data processing similar to that of a biological neural system [28, 29 & 33]. An artificial neuron consist of weight bias and activation function mainly. Each neuron receives inputs $x_1, x_2, \ldots, x_n$ attached with a weight $x_i$ showing the connection strength for a particular input for each connection as shown in Fig. 2.
Each input is then multiplied by the corresponding weight of the neuron connection and the product added to a bias \[b_i\]. A bias \(b_i\) is a type of connection weight with a constant non-zero value added to the summation of the products of inputs and corresponding weights \(w\) given as follows in equation 1.

\[ U_i = \sum_{j=1}^{n} w_{ij}x_j + b_i \]  

The summation \(U_i\) is transferred using transfer function \(f\) to yield a value called the unit’s activation given as \(y_i = f(U_i)\).

Levenberg Marquardt Algorithm (LMA), the most widely used training algorithm for multi-layer perceptron, is a gradient descent technique used to minimize error for a particular training pattern [29, 39, 40]. LMA is used to adjust the weights to a small amount at a time in order to reduce the error. The training of the network is accomplished by adjusting the weights and is carried out through a large number of epochs. The goal of the learning procedure is to find the optimal set of weights which in the ideal case would produce the right output for any input [28, 29]. Once the ANN is properly and sufficiently trained, it can generalize to similar cases which it has never seen [28, 29, 33].

The ANN consists of an input layer, hidden layers and an output layer. Training is done to modify the connection weights, in some orderly manner using a suitable learning algorithm. In ANNs, an input is fed into the network along with the desired output and the weights are then adjusted so that the network attempts to produce the desired output [29, 33]. The weights after training contain meaningful information whereas before training they are at random [41, 42]. Multilayer perceptions are the most widely used kind of ANNs. Networks with interconnections that do not form any loops are called feedforward [28, 43, 44]. Fig. 3 shows the architecture of a multi-layer neural network model.

In this work, a three layer feed-forward ANN architecture was developed to predict performance [output variables of BSFC, Combustion efficiency and Maximum pressure developed, input parameters such as engine speed, bioethanol mixture, exhaust gas temperature, and mass flow rate] of G200 IMEX spark ignition engine in relation to the input data as shown in Fig. 4.
Based on this analysis of the optimal architecture of the ANN, a model with a 4–10–2 [the number of input, neurons in hidden layers and outputs respectively] was constructed to predict the performance of the engine using the recorded data. The learning algorithm used in this work is Levenberg Marquardt Algorithms while the activation function is logistic sigmoid (logsig) transfer functions and the maximum number of epochs is 10. An epoch is a measure of the number of times all of the training vectors are used once to update the weights. For batch training, all of the training samples pass through the learning algorithm simultaneously in one epoch before weights are updated while for sequential training, all of the weights are updated after each training vector is sequentially passed through the training algorithm.

The ANN model developed in this study is used to predict the BSFC, Combustion efficiency and Maximum pressure developed by the test engine based on the mass flow rate, exhaust temperature, bioethanol mixture and engine speed. Exhaust temperature, mass flow rate, bioethanol mixture and engine speed were used as input layer parameters, while the BSFC, Combustion efficiency and Maximum pressure developed each were used separately as output layer components of the ANNs. In the ANN model, from the experimental data set 70% of the values were used for training of the network and the remaining 30% of the input data were used to test and validate the performance of the trained network. The values of the input and output parameters are given in Table 4.

**Table 4.** Sample Values of input and Output Data.

| Data no | Biofuel Mixture (%) | Exhaust Gas Temperature (%) | Engine speed (rpm) | Mass flow Rate (×10^{-5} kg/s) | Combustion Efficiency (%) | Maximum Pressure (bar) | BSFC (kg/kwh) |
|---------|---------------------|----------------------------|-------------------|--------------------------------|--------------------------|------------------------|--------------|
| 1       | 0                   | 184.3                      | 1500              | 9.716                          | 65                       | 26.785                 | 0.316        |
| 2       | 0                   | 193.5                      | 2000              | 10.464                         | 63                       | 27.323                 | 0.310        |
| 3       | 0                   | 204.1                      | 2500              | 14.201                         | 60                       | 27.944                 | 0.255        |
| 4       | 0                   | 205.6                      | 3000              | 16.443                         | 60                       | 28.032                 | 0.248        |
| 5       | 0                   | 206.4                      | 3500              | 22.422                         | 58                       | 28.079                 | 0.289        |
| 6       | 10                  | 188.1                      | 1500              | 10.511                         | 71                       | 27.007                 | 0.322        |
| 7       | 10                  | 194.2                      | 2000              | 11.262                         | 70                       | 27.364                 | 0.320        |
| 8       | 10                  | 200.8                      | 2500              | 15.016                         | 70                       | 27.751                 | 0.304        |
| 9       | 10                  | 202.8                      | 3000              | 17.268                         | 69                       | 27.845                 | 0.273        |
3. Result and Discussion

In this study, different network models were tried and their correlation coefficients were evaluated and recorded. The highest correlation coefficient for the various engine parameters were obtained at a network. The performance value for the final iteration obtained gave a superior result compared to the result obtained from other iteration processes.

|   | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|----|----|----|----|----|----|----|----|----|----|----|
|   | 10 | 203.0 | 3500 | 22.524 | 68 | 27.880 | 0.273 |
| 11 | 20 | 188.2 | 1500 | 9.883 | 80 | 27.013 | 0.300 |
| 12 | 20 | 194.7 | 2000 | 10.643 | 76 | 27.394 | 0.321 |
| 13 | 20 | 197.9 | 2500 | 12.923 | 75 | 27.581 | 0.303 |
| 14 | 20 | 200.5 | 3000 | 15.964 | 72.5 | 27.733 | 0.281 |
| 15 | 20 | 200.4 | 3500 | 17.485 | 71 | 27.728 | 0.217 |
| 16 | 30 | 188.4 | 1500 | 7.004 | 75 | 27.025 | 0.234 |
| 17 | 30 | 193.9 | 2000 | 9.338 | 73 | 27.347 | 0.250 |
| 18 | 30 | 198.2 | 2500 | 11.673 | 71 | 27.599 | 0.272 |
| 19 | 30 | 200.5 | 3000 | 14.008 | 70 | 27.733 | 0.275 |
| 20 | 30 | 200.8 | 3500 | 18.677 | 70 | 27.751 | 0.260 |

![Regression plots](image)

**Figure 5.** Regression plots for Training, Validation and Testing for combustion efficiency.
To estimate the accuracy of ANN predictions, the regression curves, the mean square error curves and the error histograms shown in Fig. 5 to Fig. 13 are employed. It was observed that a high prediction capability was achieved for training, testing and validating data sets of combustion efficiency, maximum pressure and BSFC of the engine as shown in Figs. 5, 6 and 7 respectively. Therefore, the ANN model developed has a high generalization capability. The regression values obtained for combustion efficiency, maximum pressure and BSFC are 0.996, 0.995 and 0.974 respectively.

Mean square errors (MSE) against epochs during the training process of the optimum network are plotted in which the best results for validating data set were achieved at various epochs as shown in Figs. 8, 9 and 10 for combustion efficiency, pressure developed and BSFC respectively. For combustion efficiency, the best validation performance was obtained at the mean square error value of 1.0023 at epoch 3 as shown in Fig. 8 while for maximum pressure the best validation performance is obtained at the mean square error of 0.0013284 at epoch 5 as shown in Fig. 9. Similarly, for brake specific fuel consumption, the best validation performance is obtained at the mean square error of 0.00018825 at epoch 10 as shown in Fig. 10.

![Figure 6. Regression plots for Training, Validation and Testing for In-cylinder pressure.](image-url)
Figure 7. Regression plots for Training, Validation and Testing for BSFC.

Figure 8. MSE plots of Validation performance for combustion efficiency.
The error histogram plots for training, validation and testing for the data sets of combustion efficiency, pressure developed and BSFC are given in Figs. 11, 12 and 13 respectively.

**Figure 9.** MSE plots of Validation performance for maximum cylinder pressure.

**Figure 10.** MSE plots of Validation performance for BSFC.
The result of the system showed a good agreement between the predicted values and the experimental values as shown in Figs. 14, 15 and 16. These figures showed that the experimental values and the predicted values are very close to each other. The closeness of the values revealed that the developed neural network model was able to generalize between the input variables and the output variables. Also, the correlation coefficients of 0.996, 0.995 and 0.974 obtained for combustion efficiency, pressure developed and BSFC support this claim.

Figure 11. Error Histogram for Training, Validation and Testing for Combustion Efficiency.

Figure 12. Error Histogram for Training, Validation and Testing for Pmax.
The results showed that the ANN has the capability of generalizing between engine speeds, mass flow rate, biofuels mixtures and exhaust gas temperatures of input variables and combustion efficiency and combustion pressure of output variables reasonably well.

![Error Histogram with 20 Bins](image)

**Figure 13.** Error Histogram for Training, Validation and Testing for BSFC.

**Figure 14.** Comparison of Experimental Data and ANN Predictions for Combustion Efficiency.
4. Conclusions

The performance analysis of a single cylinder spark ignition engine fuelled with ethanol – petrol blends were carried out successfully at constant load conditions. E0 (Petrol), E10 (10% Ethanol, 90% Petrol), E20 (20% Ethanol, 80% Petrol) and E30 (30% Ethanol, 70% Petrol) were used as fuel. The Engine speed, mass flow rate, combustion efficiency, maximum pressure developed, BSFC and Exhaust gas temperature values were measured during the experiment.

Using the experimental data, a Levenberg Marquardt Artificial Neural Network (ANN) algorithm and Logistic sigmoid activation transfer function with a 4–10–2 model was developed to predict the BSFC, maximum pressure and combustion efficiency of G200 IMEX spark ignition engine using the recorded engine speed, mass flow rate, bioethanol mixtures and exhaust gas temperature as input variables.
The performance of the ANN was validated by comparing the predicted data with the experimental results. The results showed that the training algorithm of Levenberg Marquardt was sufficient enough in predicting the BSFC, combustion pressure and combustion efficiency of the test engine. Correlation coefficient (R) values of 0.974, 0.996 and 0.995 were obtained for BSFC, combustion efficiency and pressure respectively. These correlation coefficient obtained for the output parameters are very close to one (1) showing good correlation between the ANN predicted results and the experimental data while the Mean Square Error (MSE) were found to be very low (0.00018825 @ epoch 10 for BSFC, 1.0023 @ epoch 3 for combustion efficiency and 0.0013284@ epoch 5 for in-cylinder pressure).

Therefore, ANN environment from MATLAB showed to be a useful tool for correlation and simulation of engine parameters. ANN provided the accurate analysis of the complex problems and the analysis of the performance of spark ignition engines.

Thus, this has proved that ANN could be used to predict performance values of internal combustion engines. In this way it would be possible to conduct time and cost efficient studies instead of expensive and long experimental study.

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Conflict of Interest

We have no conflict of interest to declare.

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