Original Research Article

ARTIFICIAL NEURAL NETWORK BASED PERFORMANCE PREDICTION SYSTEM FOR SPARK IGNITION ENGINES

Abstract

The demand for efficient and environmentally friendly spark ignition (SI) engines has driven researchers to explore advanced methods for optimizing engine performance and reducing emissions. One such method is the use of Artificial Neural Networks (ANNs) to develop predictive models that can accurately estimate engine performance under various operating conditions. This study presents the design and implementation of an ANN-based performance prediction system for spark ignition engines, focusing on critical performance metrics. An ANN based model and network architecture were developed and simulated in MATLAB neural network toolbox environment. The search for efficient network architecture was performed in terms of activation function, number of hidden layers, number of neurons in the hidden layers and the type of training function using highest regression value criteria. The ANN predicted results were validated by comparing with corresponding actual values obtained from experiments using t test. The search for efficient network architectures showed that 6 – 13 – 9 – 6 – 8 network architecture gave the best predicted results for the ANN model. Logsig activation function and trainlm training function gave reliable predicted results for the model. The results of the t test and comparison of ANN predicted results with actual experimental results showed that there is no significant difference between the two sets of results at 5% level of significance. The results also showed that 28 neurons distributed into three hidden layers have capability to map and generalize the non-linear data effectively thereby predicting the results accurately. It is concluded that the developed ANN based prediction system for SI engines is robust and capable of giving accurate results.

Keywords: Artificial Neural Network, Exhaust Gas Emissions and SI Engine, Activation Function, Regression Value.

1. INTRODUCTION

Spark Ignition (SI) engines, which rely on the combustion of a precisely controlled air-fuel mixture to generate power, are widely used in automotive and power generation industries due to their efficiency, reliability, and relatively low operating costs. However, increasing global concerns over fuel consumption, greenhouse gas emissions, and environmental sustainability have pushed researchers and manufacturers to focus on improving the performance and efficiency of these engines while simultaneously reducing emissions. Traditional methods for optimizing engine performance, such as experimental testing and model-based simulations, are time-consuming, costly, and may not fully capture the complexities of engine dynamics under varying operating conditions [1, 2, 3].

In recent years, Artificial Neural Networks (ANNs), a subset of machine learning algorithms, have emerged as a powerful tool for modeling and predicting complex nonlinear systems, including internal combustion engines. ANNs are particularly well-suited for performance prediction tasks because of their ability to learn from large datasets and identify patterns in highly nonlinear relationships between input and output parameters. These capabilities have led to their growing application in engine modeling, optimization, and control. ANNs can serve as effective alternatives to conventional predictive techniques by offering faster, more accurate predictions of engine performance metrics such as power output, fuel efficiency, and emissions, based on input variables like engine speed, load, air-fuel ratio, and ignition timing [4, 5, 6].

Several studies have demonstrated the effectiveness of ANN models in engine performance prediction. For instance, a study by [7] used an ANN to predict the performance and emissions characteristics of a gasoline engine, achieving high accuracy compared to experimental data. Similarly, [8] developed an ANN-based model to estimate engine parameters, demonstrating the potential of neural networks in optimizing engine performance across a wide range of operating conditions.

The primary motivation for developing an ANN-based performance prediction system for spark ignition engines is the need to improve engine efficiency and reduce emissions in a cost-effective and timely manner. By leveraging the predictive power of ANNs, engine designers and manufacturers can optimize engine settings in real time, enhancing fuel economy, improving power output, and minimizing harmful emissions, all while reducing the need for extensive experimental testing [9, 10, 11]. Improving the performance of internal combustion engines is one of the major concerns of researchers. Experimental studies are more expensive than computational studies. Also using computational techniques allows one to obtain all required data for the cylinder, some of which could not be measured [12, 13, 14]

The traditional approach taken to model the spark-ignition engine is to divide the cylinder contents into two thermodynamic zones, each with its own temperature and composition [15, 16]. The flame separates the cylinder content into burned zone at high temperature and unburned zone at lower temperature. Each zone is assumed to be a homogeneous mixture of N species each modeled as an ideal gas [17, 18]. Simulation is the process of designing a mathematical or logical model of a real system and then conducting computer based experiments with the model to describe, explain and predict the behaviours of the real system [19, 20, 21, 22, 23, 24].

The good ability of artificial neural networks (ANN) for modeling nonlinear phenomena (like processes occurring in spark ignition engines) because they are themselves nonlinear together with their relatively simple application procedure is the reason for their wide usage. The goal of this technique is to significantly decrease dynamometer test requirements by generating mathematical models of the output using smaller subset of dynamometer test [25, 26]. The goal is to present, while using the minimum number of experimental tests, a fast and practical simulation procedure capable of predicting performance parameters and exhaust emissions of spark ignition engines. Various approaches have been proposed for using ANN to promote modeling and calibration of engines. ANNs are suited for formulating objective functions, evaluating the specific engine performance indices with respect to the controllable engine variables and thus driving engine calibration correlation. They are computationally efficient for optimization requiring hundreds of function evaluations. [25, 27, 28, 29].

Ever tightening environmental legislation drive a significant research effort to reduce the environmental impacts of hydrocarbon fuel combustion in IC engines. However, most of these researches are based on thermodynamic and fluid dynamics models with very little effort devoted to other techniques such as artificial neural network.

2. METHODOLOGY

This study investigated the effect of varying six operating parameters on the performance characteristics of spark ignition engines using different artificial neural networks. The operating parameters that were varied are termed as input parameters while performance parameters are termed as output parameters.

Performance characteristics of SI engines using several artificial neural networks with different combinations of ANN parameters were simulated. The simulation procedure was implemented in MATLAB environment using neural network tool box.

2.1 Input Parameters.

The six input parameters considered are:

(i) Engine load

(ii) Engine speed

(iii) Equivalence ratio

(iv) Ignition timing

(v) Compression ratio

(vi) Exhaust gas recirculation

2.2 Output Parameters.

The output parameters are made up of five performance parameters and three exhaust gas emission parameters. The parameters considered are:

(i) Brake Specific fuel consumption (BSFC) - Performance parameters

(ii) Brake power (BP) - Performance parameters

(iii) Brake mean effective pressure (BMEP) Performance parameters

(iv) Thermal efficiency (η_{th}) - Performances parameters

(v) Exhaust gas temperature (T_{EG}) - Performance parameters

(vi) Unburned Hydrocarbon (HC) – Exhaust gas emission

(vii) Carbon monoxide (CO) - Exhaust gas emission

(viii) Oxides of Nitrogen (NO_X) - Exhaust gas emission

2.3 Development of Network Architecture for ANN Model

Artificial neural networks are computational models which can be used in a wide variety of situation. The most important feature of ANN is their ability to solve problem through learning by example rather than by becoming involved in the detailed characteristics of the systems. The basic element of an ANN is the neuron. Neuron model are in fact more closely related to traditional mathematical models than they are to biological models. A neuron model consists of three basic parts:

(i) Synapse or connecting Link: Each of these is characterized by a particular weight or strength of its own.

(ii) Adder: For summing the input signals, weighted by respective synapses of the neuron.

(iii) Activation function: For limiting the amplitude of the output of a neuron.

In mathematical terms, a neuron j may be described by writing the following equation:

$$y_j = \varphi\left(\sum_{i=0}^{N} W_{ji}\, x_i\right) \tag{1}$$

Where:

$y_j =$ Output of the neuron

$\varphi =$ Activation function

$W_{ji=}$ Synaptic weights

Xi = inputs to the neuron

N = Number of inputs

For a multi-layer perception (MLP) model with several neurons and several layers of neuron used in this work, certain model parameters must be selected after careful investigation. These parameters are:

1) Type of activation function

2) No of hidden layers

3) No of neurons in the hidden layers

4) Choice of training algorithm which will influence synaptic weight and bias.

In this study, ANN model has one input layer consisting of six neurons, H hidden layers consisting of N_H neurons and one output layer consisting of eight neurons

For this,

The equation connecting the input layer to the hidden layers is:

$$\left(\sum_{j=1}^{N} Wij \;\; I_j\right) \tag{2}$$

And the equation connecting the hidden layers to the output layer is

$$\sum_{j=1}^{N} W_i\varphi \tag{3}$$

To get the required ANN model, we combine equations 2 and 3

∴ The ANN model is

$$y_k = \sum_{l=1}^{N_H} W_i \, \varphi \left(\sum_{j=1}^{N} W_{ij} \, I_l\right) \tag{4}$$

Where

y_k = outputs of the ANN model

K = number of output

N_H = number of neurons in the hidden layers

H = number of hidden layers

W_i = synaptic weights connecting the hidden layers with output

W_{ij} = synaptic weights connecting the inputs to the hidden layers

N = number of inputs

φ = activation / transfer function

I_j = Inputs to the ANN model

2.4 Simulation Procedure

There were 425 engine data patterns available, which were partitioned randomly into three sets. 70% of the data were used for training the network, 15% of the data were used for validating the network and the remaining 15% of the data were used to test the network. Network training can be made more efficient if certain preprocessing steps such as normalization are performed on the network inputs and target outputs. Normalization step was applied to both the input vectors and the target vectors in the data set. The network output was then reversed transformed back into the units of the original target data. Several ANN parameters were investigated in details in order to get efficient network architecture for the ANN model. The ANN parameters considered were:

(i) **Activation / transfer function**: Three different activation functions (Purelin, Logsig and Tansig) which are the most commonly used and most accurate activation functions available from literatures were investigated.

(ii) **Number of hidden layers**: One, two and three hidden layers were considered at several levels and at different combinations.

(iii) **Number of neurons in the hidden layers**: Several iterations at several levels using different combinations of neurons were investigated.

(iv) **Training function**: Three different training functions trainlm (Levenberg – Marquardt algorithm), trainrp (Resilient back propagation algorithm) and trainscg (Scaled conjugate gradient) were investigated in details.

2.5 Statistical Analysis

All statistical tests share the same principle which is that they compare the observed or predicted results with an expected or actual value based on dataset used and come up with a test statistic. In this work, there were two sets of results, which are the actual values of output and the ANN predicted values of output. The best and most popular statistical methods for analyzing differences between two groups of dataset is t test and was therefore used in this work.

The t test gives an indication of the separateness of two sets of measurement and is thus used to check whether two sets of data are essentially different. The typical way of doing these is with the null hypothesis that means of the two sets of data are equal. The equation of t test is given below:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\frac{var1}{n} + \frac{var2}{n}} \quad (5)$$

Where

X_1 = actual values

X_2 = ANN predicted values

$\overline{X_1}$ = mean of X_1

$\overline{X_2}$ = mean of X_2

Var_1= Variance = standard deviation squared (SD^2) of X_1

Var_2= Variance =standard deviation squared (SD^2) of X_2

n = number of samples (= 425)

t = t stat (calculated value of t)

Degree of freedom = $(n_1 + n_2) – 2 = 850 – 2 = 848$

The null hypothesis is $\mu_1 - \mu_2 = 0$

This means that there is no significant difference between the two means

The confidence level used is 95% = 0.05 level of significance

The criterion is: Reject the null hypothesis if

t stat > t critical

Where, t critical = t tabulated

3 RESULTS AND DISCUSSION

Figure 1 shows the effect of number of neurons on the regression value obtained at different activation functions. From the figure, it can be seen that regression increases with increase in number of neurons from 24 neurons to 28 neurons after which regression values decreases for all the three activation functions considered. Logsig activation function gave the highest regression value followed by Tansig activation function while Purelin activation function gave the lowest regression value. The highest regression value of 0.99787 was obtained for Logsig activation function using 28 neurons while the lowest value of 0.94321 was obtained using 24 neurons. The highest percentage increase of 8.13% in the regression value was obtained for Tansig activation function when no of neurons increases from 26 to 28. This result shows that Logsig activation function gave the best output result; this may be due to the fact that sigmoid (Logsig) functions are continuous and differentiable hence they are able to fit in to non-linear data such as that encountered in SI engines.

Figure 2 shows the effect of number of neurons on regression value obtained for different no of hidden layers. It can be seen from the figure that regression value increases with increase in the number of hidden layer up to three layers. The lowest regression value of 0.71657 was obtained when one hidden layer and 18 neurons were used while the highest regression value of 0.99787 was obtained when three hidden layers and 28 neurons were used. Regression value increases from 0.71657 to 0.78431 when the number of neurons increases from 18 to 33 before reducing to 0.76321 when number of neurons increases to 38 for one hidden layer. For two and three hidden layers, regression values increase with number of neurons up to 28 neurons before deceasing again with further increase in number of neurons. The results obtained may be due to the fact that increasing the number of hidden layers up to three hidden layers usually increases the mapping capability and capacity to generalize of the neural network. Whereas, increasing the number of neurons beyond a certain limit depending on the particular network will cause over fitting and over generalization of the training data hence, its capacity to predict results accurately will be diminished.

Figure 3 shows the effect of training function on regression value using different number of neurons. From the figure, it can be seen that trainlm training function gave the highest regression values for all the different numbers of neurons considered. The lowest regression value of 0.79985 was obtained with trainscg training function and 20 neurons while the highest regression value of 0.99787 was obtained with trainlm and 28 neurons. The result obtained may be due to the fact that trainlm performs better on function fitting (nonlinear regression) problems and is the fastest (in MATLAB neural network toolbox) compared with the other two training functions. Hence it constantly gave the highest regression values.

Table 1 shows the arrangement of hidden layer neurons. From the figure, it can be seen that 28 neurons with 13 neurons in the first hidden layer, 9 neurons in the second hidden layer and 6 neurons in the third hidden layer gave the highest regression value of 0.99787. This result was obtained after several iteration steps using all the three activation functions and training functions considered. Although the table only shows the case when Logsig activation function and trainlm training function, which gave the highest regression value, were used. This result shows that the optimum network architecture was obtained when this arrangement is used.

Tables 2 to 9 present results acquired through statistical analysis using t test for two sample assuming unequal variances. The ANN predicted results were compared with actual results to check if there is significant difference between the two results. Each of the eight output parameters of the ANN predicted results were compared with their corresponding parameters from actual results using t test for the. For BSFC, t stat is -0.008474 which is less than t critical (two tail) value of 1.962765 and P (two tail) value of 0.993240 is much greater than 0.05 significance level, hence the null hypothesis which states that there is no significant difference between the ANN predicted results and the actual experimental results is accepted. For BP, P (two tail) value of 0.938225 is greater than 0.05, this means that there is 93% chance that there is no significant difference between two sets of results. For BMEP, t start value of 0.108318 is less than t critical (two tail) value of 1.962765 hence, the null hypothesis is accepted. For thermal efficiency, P (two tail) value of 0.982898 is greater than the significance level of 0.05. This means that there is 98% chance that there is no significant difference between the two sets of results; hence the null hypothesis is accepted. Exhaust gas temperature has t start value of 0.179837 which is less than t critical (two tail) value of 1.962768 hence, the null hypothesis is accepted.

HC emission has t start value of -0.137501 which is less than t critical (two tail) value of 1.962765, hence the null hypothesis is accepted since t start < t critical. For CO emission, P (two tail) value of 0.985586 is greater than the significance level of 0.05. This shows that there is 98% chance that there is no significant difference between the two sets of results; hence the null hypothesis is accepted. For NO_X emission, t start value of -0.326245 is less than t critical (two tail) value of 1.964027 hence, the null hypothesis is accepted.

The results obtained in this work is in agreement with the results obtained by [3, 26, 27, 30] and the results follow the same trend.

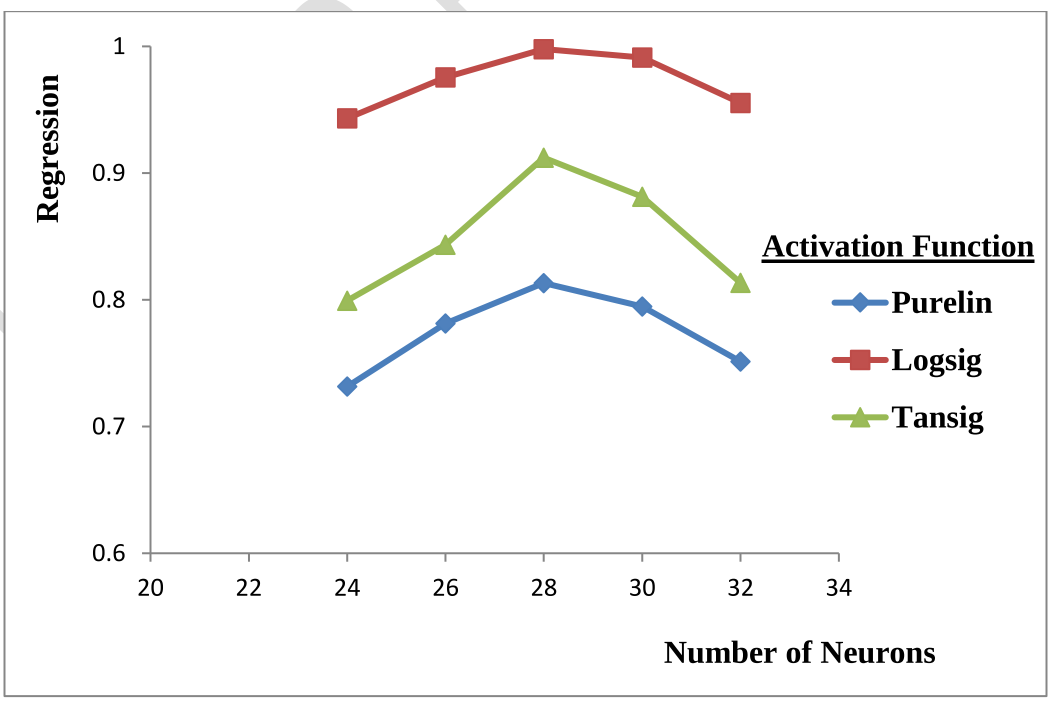

Figure 1: The Effect of Number of Neuron on Regression Value at Different Activation Function

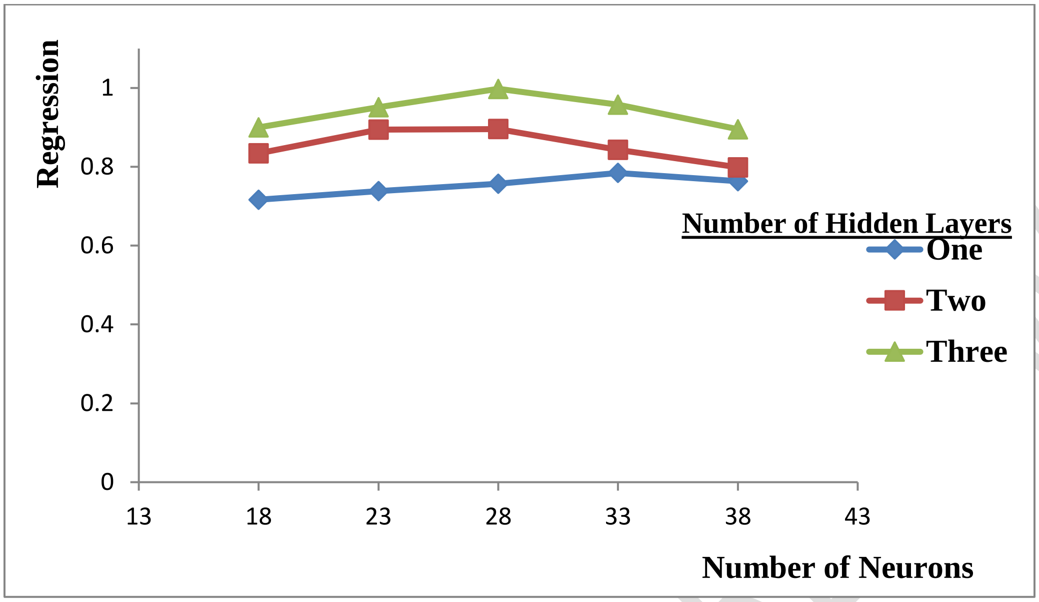

Figure 2: The Effect of Number of Neuron on Regression Value at Different Number of Hidden Layers

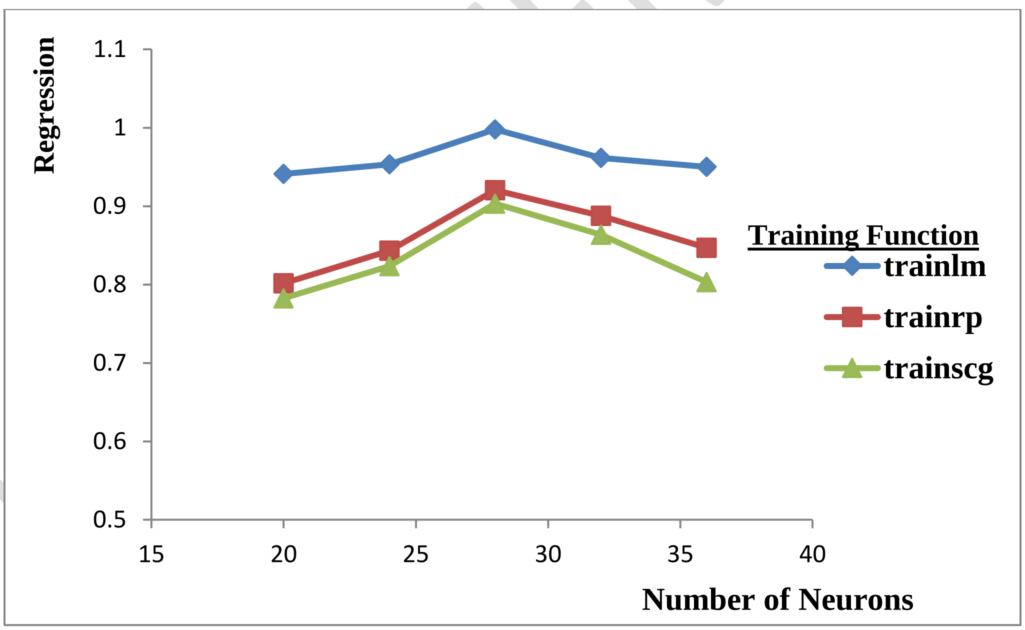

Figure 3: The Effect of Number of Neuron on Regression Value at Different Training Functions

Table 1: Hidden Layer Neurons for ANN Model

S/N	1^{st} Layer	2^{nd} Layer	3^{rd} Layer	R	Epoch (Iteration)	Time
1.	11	9	6	0.99561	661	1:31
2.	12	9	6	0.99733	734	1:44
3.	13	9	6	0.99787	848	2:05
4.	14	9	6	0.99750	346	0:55
5.	15	9	6	0.99709	604	1:41
6.	13	7	6	0.99650	852	1:55
7.	13	8	6	0.99753	572	1:24
8.	13	9	6	0.99787	848	2:05
9.	13	10	6	0.99610	393	1:06
10.	13	11	6	0.98790	743	2:11
11.	13	9	4	0.97553	367	0:56
12.	13	9	5	0.97868	329	0:54
13.	13	9	6	0.99787	848	2:05
14.	13	9	7	0.99509	846	2:18
15.	13	9	8	0.99128	522	1:37

Table 2: t Test for Brake Specific Fuel Consumption (BSFC)

	Variable 1	*Variable 2*
Mean	273.7411765	273.7589932
Variance	940.1403996	938.5539194
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	
t Stat	-0.008474134	
P(T<=t) one-tail	0.496620347	
t Critical one-tail	1.646652501	
P(T<=t) two-tail	0.993240693	
t Critical two-tail	1.962765403	

Table 3: t Test for Brake Power (BP)

	Variable 1	*Variable 2*
Mean	23.28705882	23.26896099
Variance	11.71339345	11.44848535
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	

t Stat	0.077523647
P(T<=t) one-tail	0.469112634
t Critical one-tail	1.646652501
P(T<=t) two-tail	0.938225268
t Critical two-tail	1.962765403

Table 4: t Test for Brake Mean Effective Pressure (BMEP)

	Variable 1	*Variable 2*
Mean	649.4423529	648.2381688
Variance	26074.47367	26450.76262
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	
t Stat	0.108318684	
P(T<=t) one-tail	0.456884263	
t Critical one-tail	1.646652501	
P(T<=t) two-tail	0.913768526	
t Critical two-tail	1.962765403	

Table 5: t Test for Thermal Efficiency (η_{th})

	Variable 1	*Variable 2*
Mean	22.12823529	22.1231509
Variance	12.16571032	11.73266709
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	
t Stat	0.021441198	
P(T<=t) one-tail	0.491449377	
t Critical one-tail	1.646652501	
P(T<=t) two-tail	0.982898753	
t Critical two-tail	1.962765403	

Table 6: t Test for Exhaust Gas Temperature (T_{EG})

	Variable 1	*Variable 2*
Mean	511.4070588	510.2671827
Variance	8886.463629	8187.813689
Observations	425	425
Hypothesized Mean Difference	0	

Df	847
t Stat	0.179837798
P(T<=t) one-tail	0.428661462
t Critical one-tail	1.646654627
P(T<=t) two-tail	0.857322923
t Critical two-tail	1.962768716

Table 7: t Test for unburned Hydrocarbon (HC) Emission

	Variable 1	*Variable 2*
Mean	1709.576471	1712.611868
Variance	103087.2023	104025.5799
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	
t Stat	-0.137501242	
P(T<=t) one-tail	0.445333626	
t Critical one-tail	1.646652501	
P(T<=t) two-tail	0.890667252	
t Critical two-tail	1.962765403	

Table 8: t Test for Carbon Monoxide (CO) Emission

	Variable 1	*Variable 2*
Mean	6657.294118	6658.572817
Variance	1069581.104	1058236.047
Observations	425	425
Hypothesized Mean Difference	0	
Df	848	
t Stat	-0.018071558	
P(T<=t) one-tail	0.492793009	
t Critical one-tail	1.646652501	
P(T<=t) two-tail	0.985586019	
t Critical two-tail	1.962765403	

Table 9: t Test for Oxides of Nitrogen (NO_X) Emission

	Variable 1	*Variable 2*
Mean	649.9058824	655.3514457
Variance	98947.63263	19461.25128
Observations	425	425

Hypothesized Mean Difference	0
Df	585
t Stat	-0.326245956
P(T<=t) one-tail	0.372177475
t Critical one-tail	1.647462515
P(T<=t) two-tail	0.74435495
t Critical two-tail	1.964027409

4 CONCLUSIONS

The present work investigated the performance prediction system for spark ignition engines using different artificial neural networks. ANN model and network architecture were developed and simulated in MATLAB neural network toolbox environment. Based on the various results obtained and the findings of this study, the following conclusions can be drawn.

(i) Logsig activation function has capability for mapping and predicting non-linear data better than Tansig and Purelin activation functions.

(ii) Increasing the number of hidden layers up to three increases the capacity of the network to generalize non-linear data and hence increases its ability to predict results accurately.

(iii) Trainlm training function has capability to learn non-linear data and predicts accurate results better and faster than trainrp and trainscg.

(iv) Increasing the number of neurons in the network generally increases the ability of the network to predict accurate result but beyond certain limit this ability the decreases due to overgeneralization of the non-linear data.

(v) Based on the results of this study, it can be concluded that a robust and reliable ANN prediction system for SI engines has been developed.

List of Abbreviations

SI	Spark Ignition
HC	Hydrocarbon
CO	Carbon monoxide
NO_x	Oxides of Nitrogen
BSFC	Brake Specific Fuel Consumption
BP	Brake Power

BMEP Brake Mean Effective Pressure

EGR Exhaust Gas Recirculation

ANN Artificial Neural Network

Declarations

Availability of data and material

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

5. REFERENCES

[1] Semin, Ismail A., Abubakar R and Ali. I (2008) Steady-State and Transient Simulation of Gas Temperature of Intake Part Engine Journal of Applied Sciences Research Publication 4(7): Pp.767 – 777.

[2] Kalvakala K.C,Pal P. Wu Y, Kukkadapu G, Kolodziej C, Gonzalez J.p, Waqas M.U, Liu T, Aggarwal S,K. and Som S. (2021). Numerical Analysis of fuel Effects in Advanced Compression ignition using a cooperative fuel Research Engine Computational fluid Dynamic model. Journal of Energy Resources Technology. Vol. 143(4) Pp 43-60

[3] Heywood J.B. (2018): Internal combustion engine fundamentals (2nd edition) MC Grow-Hill education New York. Pp. 999

[4] Kojima S.K. and Lovei A.T. (2004) Vehicle Exhaust Emission Measurements. http://www.unep.org/urban. Retrieved on 20 June 2011.

[5] Andwari A.M., Pesyridis A., Esfahanian V. and Said M.F.M. (2019): Combustion and emission enhancement of a spark ignition two-stroke cycle engine utilizing internal and external exhaust gas recirculation approach at low-load operation. Energies vol. 12. Pp. 609 – 625.

[6] Delvi H.A., Faheem M., Khan S.A., Kumar K.M. and Kareemullah M. (2019): Effect of Ethanol-Gasoline blends on performance, combustion and Emission characteristics of spark ignition engine. Journal of advanced research in fluid mechanics and thermal sciences. Vol. 62 (2) Pp. 209 – 220.

[8] Sellnau M.C., Matekunas F.A., Cheng C. and Lancaster D. (2000). Cylinder Pressure-Based Engine Control Using Pressing-Ratio-Management and Low- Cost Non- Intrusive Cylinder Pressure Sensors. SAE Technical Paper Series, 2000-01-0932. Pp. 91 – 115.

[9] Mohiuddin k, Kwon H, Chio M and Park S. (2021). Effect of engine compression ratio, injection Timing and exhaust gas recirculation on gaseous and particle number emissions in a light- duty diesel engine. Fuel Vol. 294 Pp 52-70

[10] Newman C.F, Battch I.J., Tiller M. (2002). Spark Ignited-Engine Cycle Simulation in Modelica. 2ndInternational Modelica Conference, proceedings, pp. 133-142.

[11] Wani M.M. (2018): Computational investigations on the performance and emission characteristics of a single cylinder spark ignition engine using petrol and methanol as its alternative fuels. Energy and power vol. 8(1). Pp. 7-15.

[12] Shehata M.S. and Razek S.M.A (2008) Engine Performance Parameters and Emission Reduction Methods for Spark Ignition Engine Engineering Research Journal 120, pp. 32-57.

[13] Narcizo G.G. and Miranda D.A. (2019). Numerical Analysis of the Air-fuel Mixture in Indirect and Direct Injection of Four-stroke Engines. *Thermal Engineering*. Vol. 18 (2) pp. 89-97

[14] Anderson I. (2002). “Cylinder Pressure and Ionization Current Modeling for Spark Ignited Engines”. Linkoping Studies in Science and Technology. Thesis No. 962.

[15] Blazek J. (2004). The Combustion Process Analysis by means of in Cylinder Pressure Measurement. International Scientific Meeting Motor Vehicles & Engines Cycles Simulations in Spark-ignition Engines. International Journal of Mechanical Engineering Education vol. 29 No. 4.

[16] Huang Y, Surawski N.C, Zhuang Y, Zhou J. I, and Hong G.(2021). Dual injection: An effective and efficient technology to use renewable fuel in spark ignition engines. Renewable and Sustainable Energy Reviews. Vol. 143 Pp 95-119

[17] Krishnamoorthi M., Malayalamurthi R., He Z. and Kandasamy S. (2019): A Review on low temperature combustion engines: Performance, combustion and emission characteristics. Renewable and sustainable energy reviews. Vol. 116, Pp. 281-295.

[18] Stthiracha S. (2006) An Analytical Model of Spark Ignition Engine for Performance Prediction. Master of Science Thesis, King Mongtiut’ Institute of Technology, North Bangkok. Pp. 43 – 54.

[19] Udayraj A.R. (2011) Artificial Neural Network and Numerical Analysis of the Heat Regenerative cycle in Porous medium Engine. International Journal of Advances in Engineering and Technology, Vol.1, No 4, Pp. 307-314.

[20] Gwilliam B.J., Kojima S.K. and Lovei A.T. (2004) Vehicle Exhaust Emission Measurements. http://www.unep.org/urban. Retrieved on 15 July 2011.

[21] Beale M.H and Demuth H.B (2010) Neural Network Toolbox tm 7 user’s Guide. The Matt Works MC. Natick U.S.A Pp. 100 – 206.

[22] Ghanim W.S., Ahmed O.K. and Ali O.M (2021). Gasoline Engine Simulation Soft-ware. A comparison Review. *Material Science and Engineering*. Vol. 176 pp. 30-45

[23] Kaplan M., Ozbey M. and Ozcan H. (2018): Numerical investigation of the effets of intake port geometry on In-cylinder motion and combustion in diesel engine. The international journal of engineering and science. Vol. 7(6). Pp. 16-26.

[24] Mashkour M.A. and Ibraheem M.H. (2018): CFD analysis of petrol internal combustion engine. Journal of university of Babylon for engineering sciences. Vol. 26(9) Pp. 132-148.

[25] Obodey. O and Ajuwa C.I (2008). Calibration of Aging Diesel Engine with Artificial Neural Networks. European Journal of Scientific Research. Vol. 24, No 4, Pp. 520 – 531.

[26] Biswal A., Kale R., Teja G.R., Baneejee S., Kolhe P and Balusanly S. (2020): An experimental and kinetic modeling study of gasoline/lemon peel oil blends for PFI engine. Fuel. Vol. 267 Pp. 367-378

[27] Najafi B., Ardabil S.F., Shamshirband S., Chau K.W. and Rabczuk T. (2018): Application of ANNs, ANFIs and RSM to estimating and optimizing the parameters that affect the yield and cost of biodiesel production. Engineering Applications of Computational Fluid Mechanics. Vol. 12 (1). Pp. 611-624.

[28] Onawunmi A.S., Fayomi O.S.I, Okolie S.T.A., Adio T.A., Udoye N.E. Samuel A.U. (2019). Determination of a Spark Ignition Engine's performance parameters using Response Surface Methodology. *Energy Procedia*. Vol. 157. pp. 1412 -1422

[29] Tahboub K. K., Barghash M., Arafeh M., and Ghazai O. (2016): An ANN – GA framework for optimal Engine Modeling. Mathematical problems in Engineering. Vol. 201b. Pp. 1-8.

[30] Esposito S., Cai L., Gunther M., Pitsch H. and Pischinger S. (2020): Experimental Comparison of combustion and emission characteristics between a market gasoline and its surrogate. Combustion and flame. Vol. 214 Pp. 306 – 322.