

## Parameter Evaluation of Spark Ignition Engine Using Artificial Neural Network

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**ABSTRACT:** Spark ignition engine, SIE is a device that operates on an open thermodynamic cycle which is used to convert the chemical energy of a fuel to mechanical energy for the purpose of power generation. Emissions from this device have been found to be a major contributory factor to global warming due to incomplete combustion and these have adverse effect on human's life and properties. This study therefore evaluated the performance parameters of SIE making full use of artificial neural network, ANN.

The effects of variation in the values of three operating parameters (engine-load, engine-speed and equivalence-ratio) of SIE on the values of two performance parameters (Brake-mean-effective-pressure, BMEP and Thermal-efficiency) were theoretically evaluated using Zeldovich mechanism and thermodynamic models for the combustion process. A 4-stroke cylinder horizontal shaft SIE coupled to a 6.0 kVA alternator (electric generator) was selected for the study and for proper loading of the engine; a locally fabricated electric load simulator was used. Under varied conditions of operating parameters, BSFC, Brake-power, BP and Exhaust-Gas-Temperature, EGT were experimentally obtained. The results were modeled for performance parameters predictions using ANN tool implemented in MATLAB 7.9 environment. The operating parameters were considered as the independent parameters while BMEP and Thermal-efficiency, were held as dependent parameters. Analysis of Variance (ANOVA) was performed on the results to establish any significant differences.

The theoretical results for maximum and minimum values of the five considered performance parameters against the values for operating parameters; engine-speed, engine-load and equivalence-ratio are; BMEP (357.0kpa, 3000rpm, 100%, 1.2) and (101.0kpa, 2000rpm, 0%, 0.8), thermal-efficiency (48.5%, 3000rpm, 0%, 0.8) and (19.5%, 2000rpm, 100%, 1.2) respectively. The results obtained for the effects in the variation of engine-load and engine-speed values on BSFC, BP and EGT showed that the lowest BSFC value of 111.0g/kWh was obtained at engine-speed of 3000rpm and engine-load of 0%. BP value peaked at engine-speed of 3000rpm and engine-load of 100% with highest value of 5.7kW while lowest value of 4.3kW was obtained at engine-speed of 4000rpm and engine-load of 0%. The highest value of 601<sup>o</sup>C was obtained at engine-speed of 4000rpm and engine-load of 100% while the lowest value of 381<sup>o</sup>C was obtained at engine-speed of 2000rpm and engine-load of 0%. The effects of variation in the values of the operating parameters on performance parameters of SIE using ANN showed an improved result as ANOVA performed on its results and that of the experimental and theoretical results showed no significant difference at  $p = 0.05$  confidence level.

The study has revealed the effects of variation in the values of the selected operating parameters on performance parameters of SIE using ANN. It also developed regression models which can be used to predict the SIE performances without consuming much time.

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### I. INTRODUCTION

Increased concern about rising fuel prices, limited petroleum supplies and greenhouse-gas emissions, the call for more advanced, efficient and cleaner spark ignition engines, SIE for industrial and domestic usages is louder than ever. The number of spark ignition engines (electric generators) in Nigeria is increasing every day and the primary fuels which are used in these engines (gasoline and diesel) are derived from petroleum-based crude oil. High energy costs and concerns about greenhouse gas emissions have been a motivation for the quest for more efficient internal combustion engines. The need for efficiency improvements and low emissions put

compression ignition engine (CIE) in the spotlight due to their already higher efficiency compare to Spark Ignition Engines. According to Zoran (2013) the spark ignition engines manufacturing industries is going through a period of rapid transformation. The impetus for innovation and development of advanced technologies is created by recognition of energy supply and climate change challenges, as well as awareness of market pressures and ever-increasing consumers' expectations. However, researchers' contributions to the field of energy management include simulation studies using predictive modeling tools, theoretical analyses, advanced experimentation and a combination of any of these. While high efficiency had been their primary focus, emissions and environmental impacts also have to be considered and be given high priority. High efficiency clean combustion strategies, such as homogeneous charge compression ignition (HCCI) and premixed charge compression ignition (PCCI), have been widely investigated in light-duty diesel engines. These advanced combustion strategies are of intense interest because they have the potential to significantly reduce engine emissions of particulate matter (PM) and nitrogen oxides (NOx). Zhiming *et al.*, (2012) noted that a typical PCCI management strategy utilizes combinations of high exhaust gas recirculation (EGR), EGR temperature control and modified fuel injection pressure and timing to create the necessary in-cylinder conditions for achieving the required burn trajectory. Some studies have also focused on the best ways to manage transitions between modes under transient conditions. Thus, integration of the engine management system in the automation structure has been achieved using standardized Maximum Transmission Unit, MTU interface modules. Evaluating SIE performance as related to exhaust gas system putting into consideration the performance parameters becomes a necessity as this will assist in controlling engine operation, engine efficiency and performance as well as extended the scope of applications to enhance a safer and conducive environment that is free of pollutants and reduced intensity of ultraviolet rays.

## II. OBJECTIVES

The aim of this study was to evaluate the performance parameters of spark ignition engine using theoretical, experimental ANN methods.

The specific objectives are:

- i. To determine theoretically some selected performance parameters of SI engine
- ii. To determine experimentally some selected performance parameters of SI engine
- iii. To predict the performance parameters of SI engine using Artificial Neural Network (ANN)
- iv. To model the results obtained through theoretical, experimental and ANN methods for speedy prediction of the selected SI engine performance parameters.

## III. RESEARCH METHODOLOGY

In this work, theoretical evaluation, experimental evaluation, prediction of performance parameters using ANN and statistical evaluation of SI engine were performed. The results of the theoretical evaluation and experimental evaluation were then compared with the corresponding results from ANN prediction to validate the accuracy of the results. In this work, theoretical analysis, experimental analysis, simulation using ANN and statistical analysis of SI engine were performed. For the purpose of theoretical analysis of SI operation, a two-zone quasi-dimensional cycle model was used. The results of the model were compared with experimental data to demonstrate the validity of the model.

### Mean effective pressure

The cylinder pressure ( $\Delta P$ ) after the start of combustion changes due to the pressure rise, due to combustion ( $\Delta P_c$ ) and a pressure change due to the volume change ( $\Delta P_v$ ).

$$\Delta P = \Delta P_c + \Delta P_v \quad 1$$

As the crank angle ( $\theta$ ) increases to its next value ( $\theta_{i+1}$ ), the volume changes from  $V_i$  to  $V_{i+1}$ , and the pressure changes from  $P_i$  to  $P_{i+1}$ . The pressure changes can be modeled by a polytropic process with an exponent K. substituting for  $\Delta P_v$  in eq. 3.11

$$P_{i+1} - P_i = \Delta P_c + P_i \left[ \left( \frac{V_i}{V_{i+1}} \right)^K - 1 \right] \quad 2$$

From which  $\Delta P_c$  can be evaluated:

$$\Delta P_c = P_{i+1} - P_i \left[ \left( \frac{V_i}{V_{i+1}} \right)^K \right] \quad 3$$

The pressure rise has to be referenced to a datum volume for example the clearance volume ( $V_c$ ) at tdc because  $\Delta P_c$  is not directly proportional to mass fraction burned since combustion process is not occurring at constant volume.

$$\Delta P_c^* = \Delta P_c V_i / V_c \quad 4$$

Where  $\Delta P_c^*$  is the pressure rise due to combustion referenced to datum at  $V_c$

The end of combustion occurs after N increment when the pressure rise due to combustion becomes zero. The reference pressure rise due to combustion is proportional to the mass fraction burned (mfb) then,

$$(\text{mfb}) = \frac{\sum_0^1 \Delta P_c^*}{\sum_0^N \Delta P_c^*} \quad 3.15$$

### Combustion process modeling

The combustion chamber is divided into two zones which are the burned zone and the unburned zone. The two zones are separated by a flame front.

The mass burning rate was modeled by equation 3.16:

$$\frac{dM_b}{dt} = A_{fl} \cdot e^{ST} \quad 3.16$$

The turbulent flame front speed (ST) was modeled by equation 3.17:

$$ST = SL \cdot f \cdot \frac{(e_u/e_b)}{[(e_u/e_b) - 1] \times M_b + 1} \quad 3.17$$

Where f is a turbulent flame factor defined by equation 3.18:

$$f = 1.0018 \times rpm \quad 3.18$$

The heat interaction between the burned and unburned zones in the combustion chamber was modeled by equation 3.19:

$$\frac{-dQ_{ht}}{dt} = A \left[ 0.26 \frac{k}{B} \left( \frac{V_p \cdot B}{\mu} \right)^{0.7} (T - T_w) + 0.69 \sigma (T^4 - T_w^4) \right] \quad 3.19$$

The gas pressure and temperature during the compression stage are calculated using equation 3.20 and 3.21

$$\frac{dp}{d\theta} = \left[ - \left( 1 + \frac{R}{C_v} \right) \cdot P \cdot \frac{dv}{d\theta} - \frac{R}{C_v} \cdot \frac{dQ_{cr}}{d\theta} + \frac{R}{C_v} \cdot \frac{dQ_{ht}}{d\theta} \right] \quad 3.20$$

$$\frac{dT}{d\theta} = T \cdot \left( \frac{1}{p} \cdot \frac{dp}{d\theta} + \frac{1}{V} \cdot \frac{dV}{d\theta} \right) \quad 3.21$$

The cylinder pressure and the temperature of burned and unburned zones was modeled using equations 3.22, 3.23 and 3.24

$$\frac{dT_u}{d\theta} = \frac{1}{N_u \cdot C_{p,u}} \cdot \frac{dQ_{ht,u}}{d\theta} + \frac{V_u}{N_u \cdot C_{p,u}} \cdot \frac{dp}{d\theta} - \frac{1}{N_u \cdot C_{p,u}} \cdot \frac{dQ_{cr,u}}{d\theta} \quad 3.22$$

$$\frac{dT_b}{d\theta} = \frac{P}{N_b \cdot R} \cdot \left[ \frac{dV}{d\theta} - \left( \frac{R \cdot T_b}{P} - \frac{R \cdot T_u}{P} \cdot \frac{MW_b}{MW_u} \right) \cdot \frac{dN_b}{d\theta} - \frac{V_u \cdot R}{P \cdot C_{p,u}} \cdot \frac{dP}{d\theta} - \frac{R}{P \cdot C_{p,u}} \cdot \frac{dQ_{ht,u}}{d\theta} + \frac{R}{P \cdot C_{p,u}} \cdot \frac{dQ_{cr,u}}{d\theta} + \frac{V}{P} \cdot \frac{dP}{d\theta} \right] \quad 3.23$$

$$\frac{dP}{d\theta} = \frac{\left[ P \frac{dV}{d\theta} \cdot \left( 1 + \frac{C_{v,b}}{R} \right) + \left( \frac{C_{v,u}}{C_{p,u}} - \frac{C_{v,b}}{C_{p,u}} \right) \cdot \frac{dQ_{ht,u}}{d\theta} + \left( e_b - e_u \cdot \frac{MW_b}{MW_u} \right) \cdot \frac{dN_b}{d\theta} \right]}{\left[ \frac{C_{v,u}}{C_{p,u}} \cdot V_u - \frac{C_{v,b}}{C_{p,u}} \cdot V_u + \frac{C_{v,b}}{R} \cdot V \right]}$$

$$- \frac{\left( C_{v,b} \cdot \left( T_b - T_u \cdot \frac{MW_b}{MW_u} \right) \right) \cdot \frac{dN_b}{d\theta} + \left( \frac{C_{v,u}}{C_{p,u}} - \frac{C_{v,b}}{C_{p,u}} \right) \cdot \frac{dQ_{cr,u}}{d\theta} + \frac{dQ_{cr}}{d\theta} - \frac{dQ_{ht}}{d\theta}}{\left[ \frac{C_{v,u}}{C_{p,u}} \cdot V_u - \frac{C_{v,b}}{C_{p,u}} \cdot V_u + \frac{C_{v,b}}{R} \cdot V \right]} \quad 3.24$$

(Suvendu and Om Prakash, 2013)

A computer program was written to solve the thermodynamic models. Equations 3.20 to 3.24 were solved by the Runge-Kutta method using MATLAB software.

### Experimental Analysis

A 4-stroke cylinder horizontal shaft spark ignition engine coupled to a 6.0kVA alternator (electric generator) was used to conduct the experiments. The engine was run on 100% petrol fuel. Some modifications were made on the SI engine's fuel supply line to allow fuel consumption (FC) and engine speed to be measured. Table 1 shows the engine's specification for the engine that was used.

**Table 1: Engine Specifications**

S/N	Parameters	Value
	Maker	Elepaq
	Type	Air cooled, SI engine
	Number of cylinder	1
	Bore –Stroke (mm)	60 x 42 mm
	Connecting rod	78 mm
	Displacement	118 cm <sup>3</sup>
	Clearance volume	10.05 cm <sup>3</sup>
	Cycle	Four stroke
	Maximum speed	5500 rpm
	Maximum torque	7.4 Nm
	Maximum power	7.0 kW
	Dimension	305 x 341 x 318 mm
	Dry weight	13 kg

### Materials and apparatus

The following materials and apparatus were used for the experiment in this research;

Elepaq 6.0kVA electric generator  
 Hydra PT-110 Non-contact laser Tachometer  
 Locally fabricated electric load simulator  
 Burette  
 Retort stand  
 Fuel tank  
 Hose  
 Petrol fuel  
 Fuel tank stand  
 Stop watch  
 Thermocouple  
 Torque meter

### Engine load

A locally fabricated electric load simulator was used in this section. This load simulator consist of twenty nine different light bulbs of 200 W each and two light bulb of 100 W (total of 6.0kW) wired in parallel, with every two bulbs sharing a switch, to allow easy loading and flexible testing. A schematic diagram of the load simulator is illustrated in Figure 1.

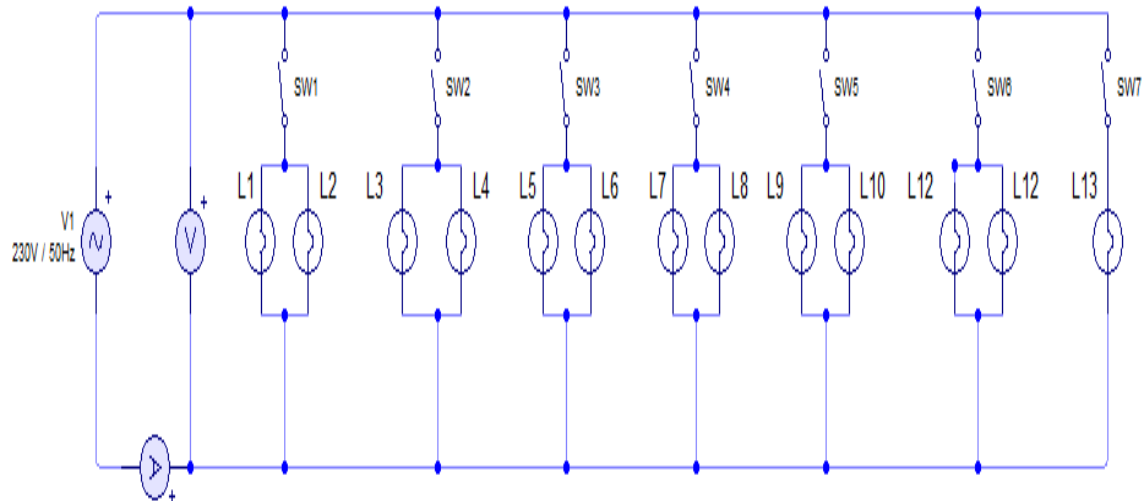


Figure 1: Circuit Diagram of the Load Simulator

### Engine speed

Five different engine speeds were considered (2000, 2500, 3000, 3500 and 4000) in this section. The actual speed in rpm was measured by using a hand hold PT-110 Non-Contact Laser Tachometer.

### Specific fuel consumption

The fuel consumption was measured by using a calibrated burette and a stop watch. The amount of fuel consumed for every two minutes was obtained and recorded. i.e.,

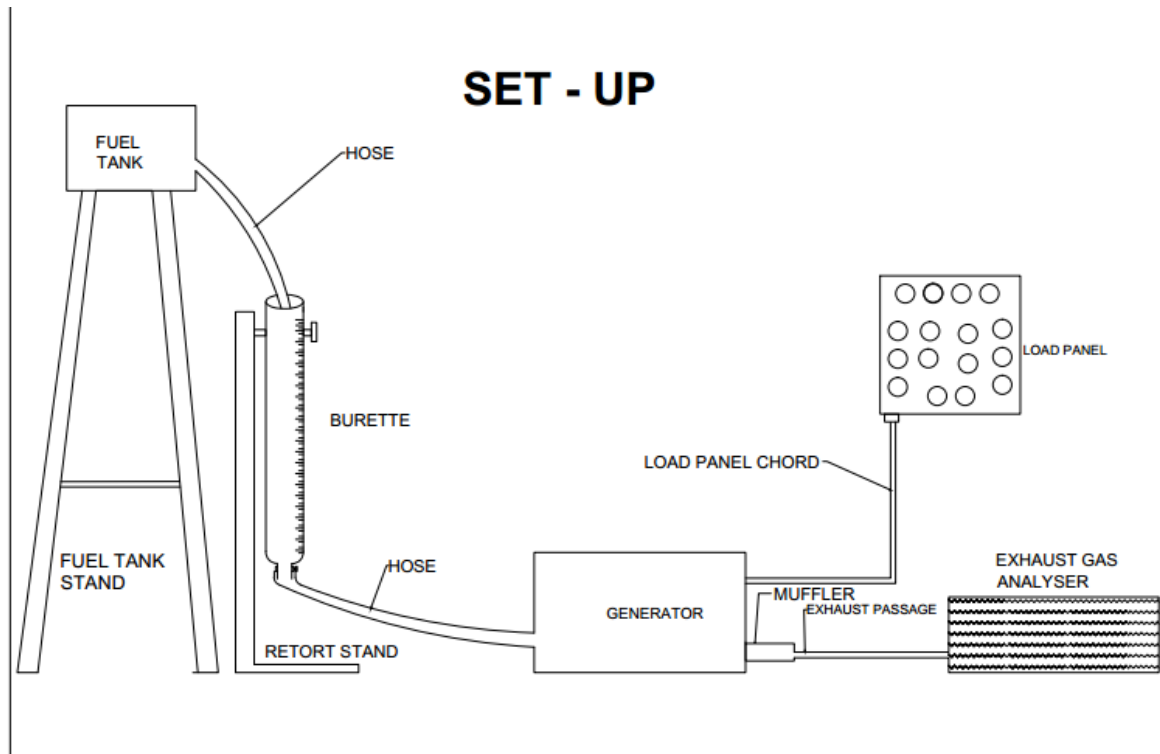
$$x_{ml/2minutes} = \frac{x}{120} \text{ ml/s} \quad 3.25$$

### Experimental procedures

The experiment set up that was used is shown in Figure 2. Before each set of data was taken, the engine was allowed to run for about 20 minutes to warm up. Procedures for collecting each data point are as follows: The engine speed was set at 2000rpm using tachometer to get the actual speed at zero (0%) loading condition (0watts). Then, fuel consumption per every 2 minutes, engine torque, exhaust gas temperature, ammeter reading and voltmeter reading were measured and recorded. Engine load was then increased from 0watts (0%) to 6.0kW (100%) in steps of 1.5kW (25%) and the above measurements were repeated. Engine speed was then increased from 2000rpm to 4000rpm in steps of 500rpm and the above procedures were repeated.

### Prediction of performance parameters using ANN

Investigation was made on the effect of varying three 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.



**Figure 2:** Experimental Set-up

### Input parameters

The input parameters that were considered are:

- (i) Engine load
- (ii) Engine speed
- (iii) Equivalence ratio

### Output parameters

The output parameters are made up of two performance parameters. The parameters that were considered are:

- i. Brake mean effective pressure (BMEP)
- ii. Thermal efficiency ( $\eta_{th}$ )

The ANN model is

$$y_k = \sum_{l=1}^{N_H} W_l \varphi \left( \sum_{j=1}^N W_{lj} I_j \right) \quad 3.26$$

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

$W_l$  = synaptic weights connecting the hidden layers with output

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

N = number of inputs

$\varphi$  = activation / transfer function

$I_j$  = Inputs to the ANN model

### ANN prediction procedure

All the engine data patterns available from theoretical and experimental results were partitioned randomly into three sets. 70% of the data was used for training the network, 15% of the data will be used for validating the network and the remaining 15% of the data was 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. Equation 3.26 shows the ANN model used in this work

Several ANN parameters were investigated in details in order to get efficient network architecture for the ANN model. The ANN parameters that were considered are:

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 and log sig was picked and used.

Number of hidden layers: One, two and three hidden layers were considered at several levels and at different combinations using literature as guide.

Training function: Three different training functions trainlm (Levenberg – Marquardt algorithm), trainrp (Resilient back propagation algorithm) and trainscg (Scaled conjugate gradient) were investigated using literatures as guide and trainlm was picked and used in this work.

Number of neurons in the hidden layers: Several iterations at several levels using different combinations of neurons were investigated in details after which 12 neurons, 8 neurons and 5 neurons in the first, second and third hidden layers respectively gave the best result and was therefore used in this work. Appendix A is the ANN code used for this study while appendix B is the ANN predicted results.

### Statistical Analysis

All statistical tests shared the same principle which means that they compare the observed or predicted results with an expected or actual value based on dataset used and come up with a so – called test statistic.

In this work, there were three sets of results, which are the theoretical, experimental and the ANN predicted results. 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 to test variance between (1) theoretical and ANN predicted result and (2) experimental and ANN results.

The t-test gives an indication of the separateness of two sets of measurement and 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:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{var_1}{n} + \frac{var_2}{n}}} \quad 3.27$$

Where

$X_1$  = experimental or theoretical values

$X_2$  = ANN predicted values

$\bar{X}_1$  = mean of  $X_1$

$\bar{X}_2$  = 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

$t$  = t stat (calculated value of  $t$ )

Degree of freedom =  $(n_1 + n_2) - 2$

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

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

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

The criterion is: Reject the null hypothesis if

$t \text{ stat} > t \text{ critical}$

Where,  $t \text{ critical} = t \text{ tabulated}$

Regression equations and  $R^2$  values were also generated for the results using historical data design tool of Design Expert 6.0.8. However, the data involved in this study were too voluminous to be analysed manually, this made it necessary to employ the use of statistical software packages developed (SPSS 17.0) to assist in the analyses of t-test to enhance speed and accuracy.

## IV. RESULTS AND DISCUSSIONS

### Theoretical Evaluation

The effects of variation in the values of three operating parameters of SI engine on the values of two performance parameters were evaluated in this section. Table 2 shows the theoretical results obtained in this work. It can be seen from this table that BMEP peaked at engine speed of 3000rpm, engine load of 100% and equivalence ratio of 1.2. The maximum BMEP value of 357.0kPa was obtained at engine speed of 3000rpm, engine load of 100% and equivalence ratio of 1.2 while the lowest value of 101.6kpa was obtained at engine speed of 2000rpm, engine load of 0% and equivalence ratio of 0.8. Thermal efficiency reduces with increase in both engine load and equivalence ratio but peaked at engine speed of 3000rpm. The highest thermal efficiency

of 48.5% was achieved at engine speed of 3000rpm while the lowest value of 19.5% was achieved at engine load of 100%, equivalence ratio of 1.2 and engine speed of 2000rpm.

**Table 2 Theoretical Results**

S/N	Load (%)	Speed (rpm)	Equivalence Ratio	BMEP (kPa)	Thermal Efficiency (%)
1.	0	2000	0.8	101.6	39.5
2.	0	3000	0.8	161.5	48.5
3.	0	4000	0.8	108.0	42.5
4.	50	2000	0.8	165.0	35.0
5.	50	3000	0.8	215.0	45.5
6.	50	4000	0.8	165.4	38.0
7.	100	2000	0.8	207.5	32.0
8.	100	3000	0.8	268.0	42.0
9.	100	4000	0.8	224.0	36.1
10.	0	2000	1.0	131.0	33.5
11.	0	3000	1.0	191.0	44.0
12.	0	4000	1.0	137.5	37.5
13.	50	2000	1.0	194.5	30.5
14.	50	3000	1.0	244.0	40.2
15.	50	4000	1.0	193.5	35.0
16.	100	2000	1.0	247.5	27.5
17.	100	3000	1.0	297.0	38.0
18.	100	4000	1.0	254.0	32.5
19.	0	2000	1.2	191.5	25.0
20.	0	3000	1.2	251.0	35.0
21.	0	4000	1.2	198.5	29.0
22.	50	2000	1.2	253.0	22.0
23.	50	3000	1.2	305.0	32.0
24.	50	4000	1.2	254.0	26.1
25.	100	2000	1.2	307.0	19.5
26.	100	3000	1.2	357.0	29.1
27.	100	4000	1.2	314.5	27.0

The results obtained in this section may be due to the fact that the mean effective pressure peaks slightly rich of stoichiometric (between equivalence ratio of 1.0 and 1.2). For lean mixtures, the theoretical fuel conversion efficiency increases linearly as equivalence ratio decreases below 1.0 and products of combustion will be at lower temperature. Thermal efficiency increases as equivalence ratio decreases provided the mixture is not too lean.

### Experimental Evaluation

The effects in the variation in the values of engine load and engine speed on brake specific fuel consumption, BSFC and exhaust gas temperature, EGT were presented in Table 3 and evaluated in this section. It can be seen from Table 3 that BSFC has minimum value at engine speed of 3000rpm and this value increase with increase in engine load. Lowest BSFC value of 111.0g/kWh was obtained at engine speed of 3000rpm and engine load of 0%. This result may be due to fact that engine friction increases rapidly above engine speed of 3000rpm leading to increase in BSFC.

**Table 3: Experimental result**

S/N	Load (%)	Speed (rpm)	BSFC (g/kWh)	EQT ( $^{\circ}$ C)
1.	0	2000	118.5	381
2.	0	2500	116.5	427
3.	0	3000	111.0	433
4.	0	3500	116.0	457



5.	0	4000	121.0	482
6.	25	2000	132.0	411
7.	25	2500	124.0	437
8.	25	3000	118.0	461
9.	25	3500	123.0	486
10.	25	4000	128.0	511
11.	50	2000	139.5	441
12.	50	2500	131.5	466
13.	50	3000	125.5	441
14.	50	3500	130.5	517
15.	50	4000	135.5	541
16.	75	2000	147.5	471
17.	75	2500	139.0	496
18.	75	3000	133.0	421
19.	75	3500	138.0	546
20.	75	4000	143.0	571
21.	100	2000	155.5	501
22.	100	2500	146.5	526
23.	100	3000	140.5	551
24.	100	3500	145.5	576
25.	100	4000	150.0	601

This table also shows that exhaust gas temperature increases as both engine speed and engine load increase. The highest value of 601<sup>0</sup>C was obtained at engine speed of 4000rpm and engine load of 100% while the lowest value of 381<sup>0</sup>C was obtained at engine speed of 2000rpm and engine load of 0%. This result may be because engine friction increases with increase in engine speed leading to maximum temperature at highest speed.

#### ANN Evaluation

The effects of variation in the values of three operating parameters on two performance parameters of SI engine were presented and discussed in this section. The operating parameters of concern are engine speed, engine load and equivalence ratio while the performance parameters considered are BMEP and Thermal efficiency, Figure 3 shows the effects of engine speed and equivalence ratio on BSFC. This Figure shows that engine speed of 3000rpm gives the lowest value for BSFC and the value increases before and after this speed for all the equivalence ratios considered. From this figure, it can also be seen that BSFC increases as equivalence ratio increases from 0.8 to 1.2. The lowest value of BSFC of 125g/kWh was achieved at equivalence ratio of 0.8 and engine speed of 3000rpm while the highest value of 165g/kWh was achieved at engine speed of 2000rpm and equivalence ratio of 1.2. Figure 3 shows the effects of engine load and equivalence ratio on BSFC. From this figure it can be seen that there exist a direct proportional relationship between BSFC and engine load, i.e., BSFC values increase as engine load increases from 0% to 100% for all the equivalence ratios considered. The

lowest BSFC value of 105g/kWh was obtained at engine load of 0% and equivalence ratio of 0.8 while the highest value of 160g/kWh was obtained at engine load of 100% and equivalence ratio of 1.2.

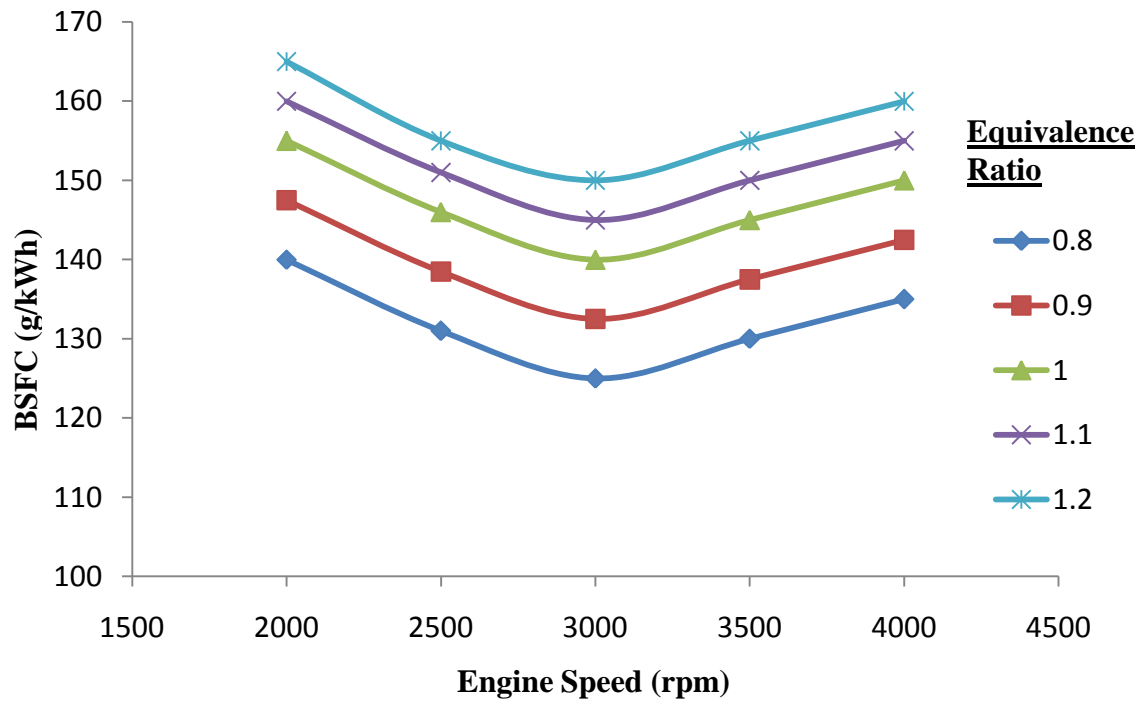


Figure 4.1: Effect of Engine Speed and Equivalence Ratio on BSFC

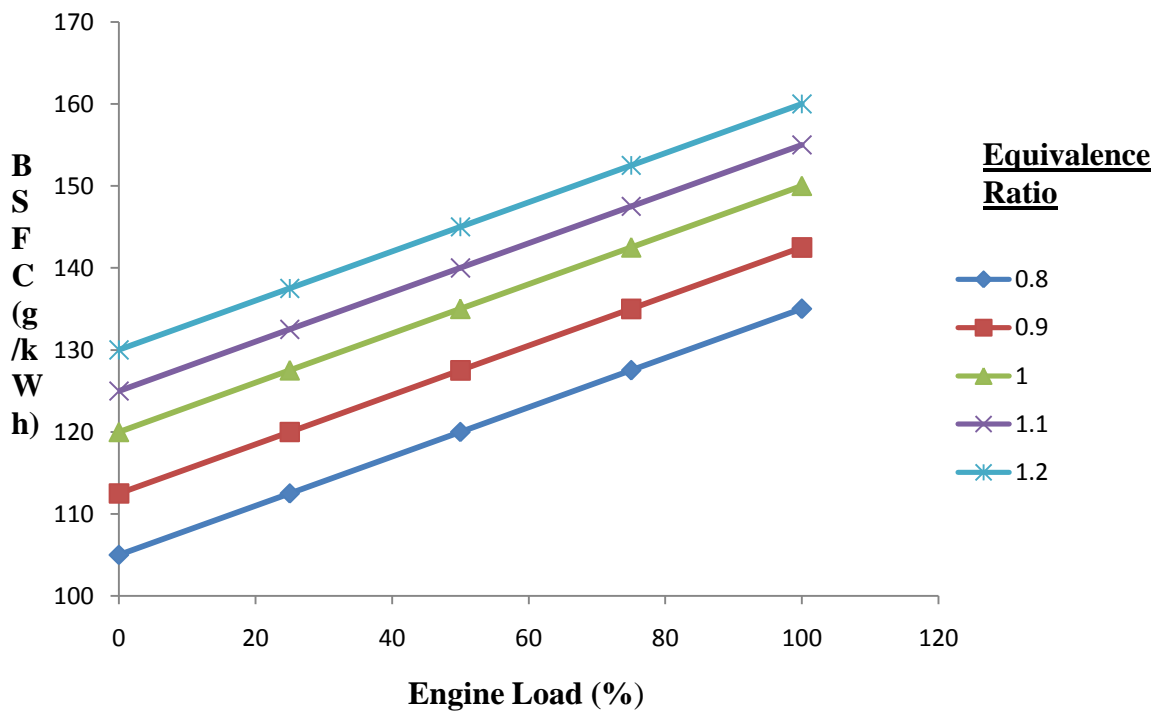


Figure 4: Effect of Engine Load and Equivalence Ratio on BSFC

Figure 4 may be due to the fact that as engine speed increase, both engine efficiency and engine friction predominates at higher speeds above 3000rpm. Hence, highest net engine efficiency is obtained at engine speed of 3000rpm. This trend is repeated for BP, BMEP and thermal efficiency. Figure 5, shows that engine speed of 2000rpm gives the lowest value for BP. The value obtained increase to maximum at 3000rpm and decreases from 3000rpm to 4000rpm for different equivalence ratio considered. It can be seen from this figure that the BP increases as the equivalence ratio increased from 0.8 to 1.2. The highest value of BP of 6.6kW was obtained at engine speed of 3000rpm and equivalence ratio of 1.2 while the lowest value of 3.8kW was obtained at engine speed of 2000rpm and equivalence ratio of 0.8. Figure 4.4 shows the effect of engine load on BP at different equivalence ratio. From this figure, it can be seen that BP increase with increase in both engine speed and equivalence ratio. The lowest BP value of 3.0kW was obtained at engine load of 0% and equivalence ratio of 0.8 and highest BP value of 6.0kW was obtained at equivalence ratio of 1.2 and engine load of 100%. The results obtained may be because increase in engine load leads to increase in engine efficiency due to better combustion which means that highest engine load leads to better combustion. Also, increasing engine load reduces the relative importance of engine friction and heat transfer. This same trend is repeated for most of the performance parameters considered in this study. Figure 6 shows that the values obtained for BMEP values peaked at engine speed of 3000rpm for all the equivalence ratios considered. Also BMEP values increase as equivalence ratio increased from 0.8 to 1.2 for different engine speeds considered. The highest BMEP value of 356.7kPa was obtained at equivalence ratio of 1.2 and engine speed of 3000rpm while the lowest value of 216.7kPa was obtained at equivalence ratio of 0.8 and engine speed of 2000rpm. Figure 7 shows that increase in engine load leads to increase in BMEP for the entire equivalence ratio considered. Highest

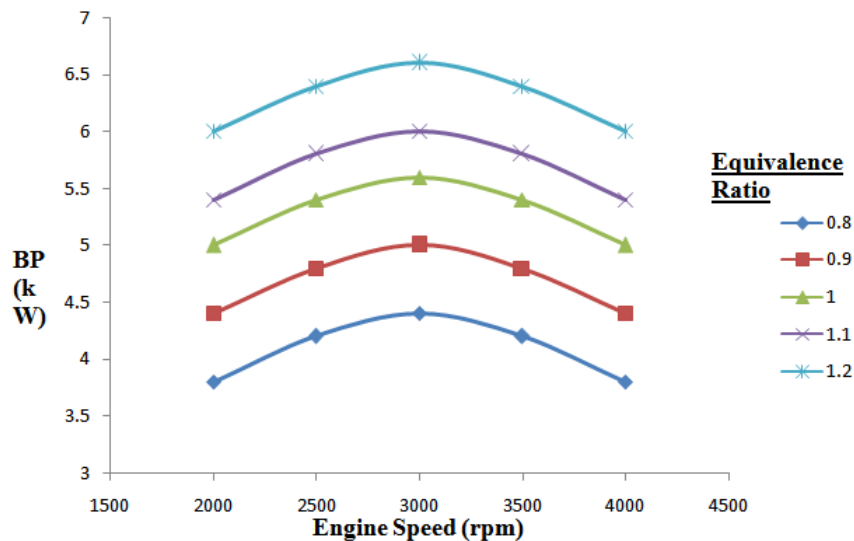


Figure 5: Effect of Engine Load and Equivalence Ratio on BP

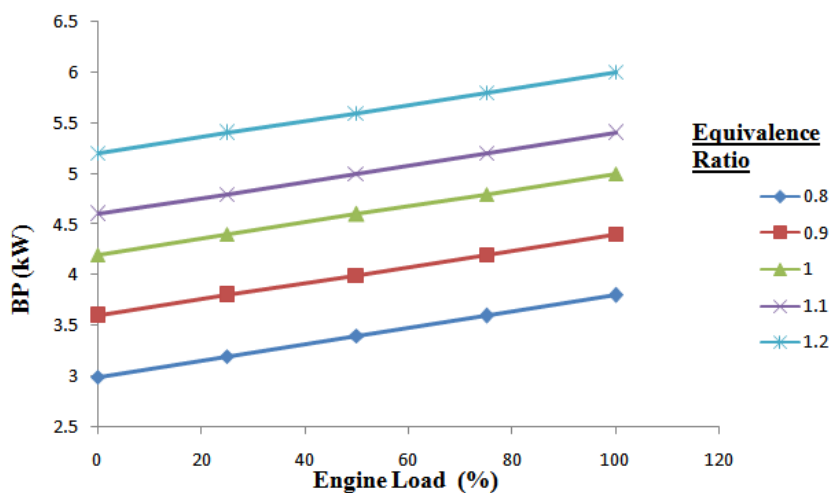


Figure 4.5: Effect of Engine Speed and Equivalence Ratio on BP

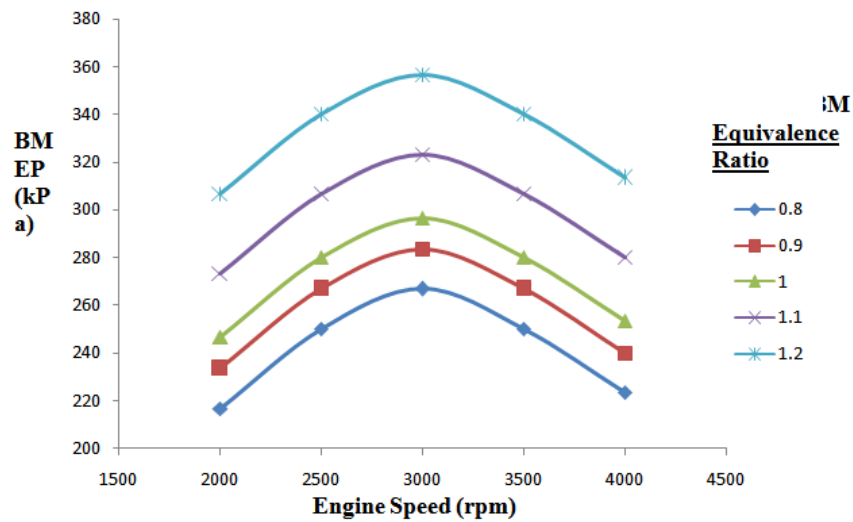


Figure 6: Effect of Engine Speed and Equivalence Ratio on BMEP

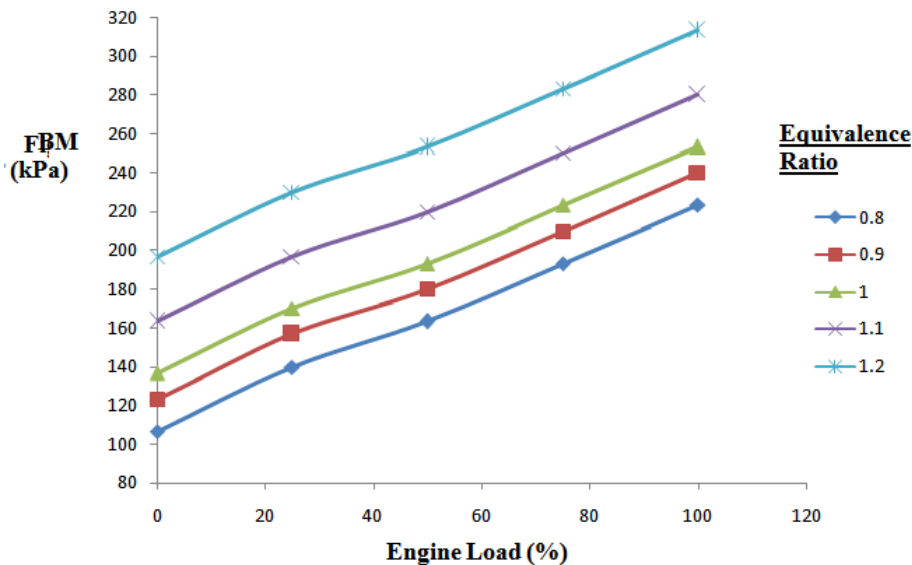


Figure 7: Effect of Engine Load and Equivalence Ratio on BMEP

BMEP value of 313.3kPa was obtained at engine load of 100% and equivalence ratio of 1.2 while the lowest value of 166.7 kPa was obtained at engine load of 0% and equivalence ratio of 0.8. Figure 4.7 shows the effects of engine speed and equivalence ratio on thermal efficiency. It can be seen from this figure that thermal efficiency reduces as equivalence ratio increases from 0.8 to 1.2 and that the values of thermal efficiency peaked at engine speed of 3000rpm for all the equivalence ratios considered. The highest value of 42% was obtained at equivalence ratio of 0.8 and engine speed of 3000rpm while the lowest value of 18% was obtained at engine speed of 2000rpm and equivalence ratio of 1.2. The highest percentage increase of 33% in thermal efficiency was obtained when equivalence ratio reduces from 1.2 to 1.1. Figure 4.8 shows that thermal efficiency reduces with increase in engine load for all the equivalence ratio considered. The highest value of 42% was obtained at engine load of 0% and equivalence ratio of 0.8 while the lowest value of 22.5% was obtained at engine load of 100% and equivalence ratio of 1.2. This indicates that there exist an inversely proportional relationship between thermal efficiency and engine load for all the considered equivalence ratios.

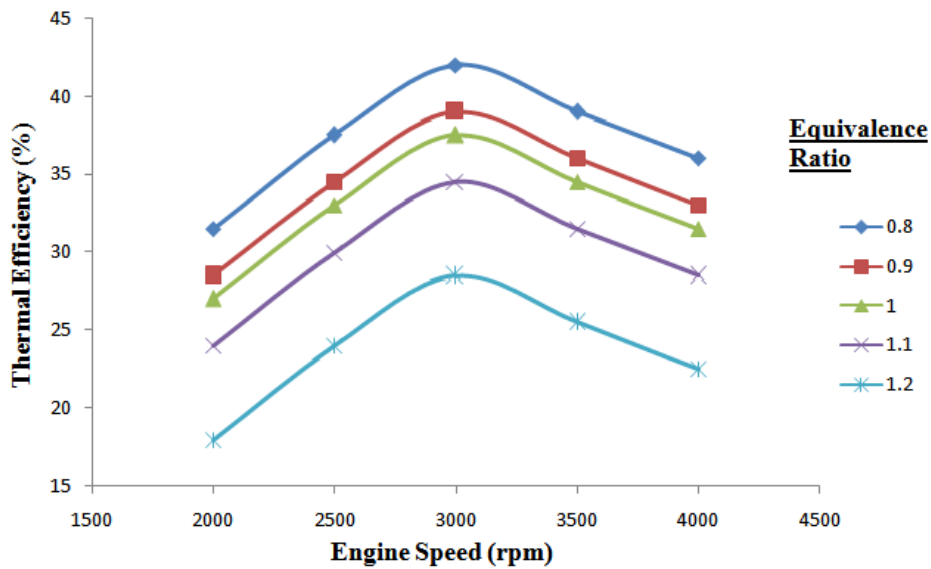


Figure 8: Effect of Engine Speed and Equivalence Ratio on Thermal Efficiency

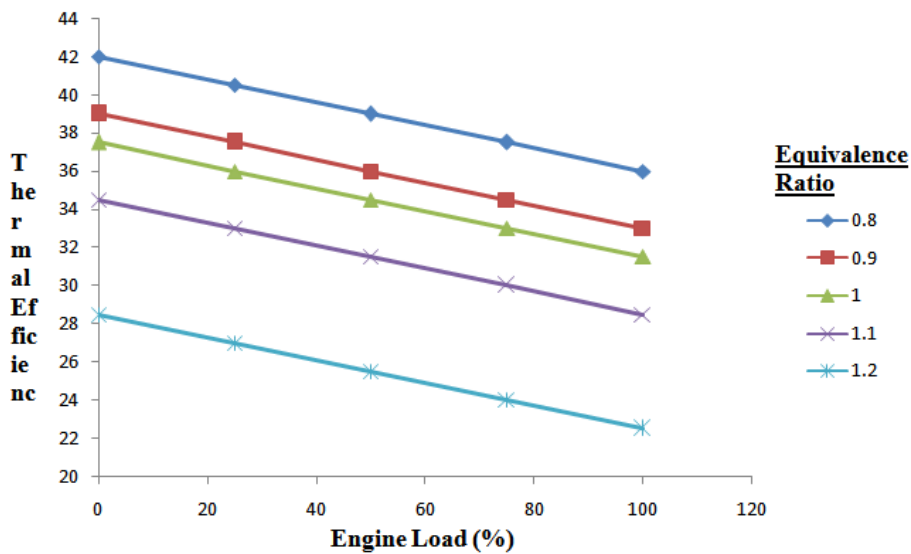


Figure 9: Effect of Engine Load and Equivalence Ratio on Thermal Efficiency

**Statistical Evaluation**

In this section ANN predicted results were compared with their corresponding results obtained from theoretical and experimental evaluations using t-test for two samples assuming unequal variances.

**t-test for ANN and theoretical results**

Table 4.3 shows the summary of t-test results obtained during comparison of ANN with theoretical results. From this table, it can be seen that for BMEP t stat value of 0.1083186 is less than t critical (two tail) value of 1.9627654 hence, the null hypothesis is accepted. For thermal efficiency, p(two tail) value of 0.9828987 is greater than the significance level of 0.05. This indicates that there is 98% chance that there is no significant difference between the two sets of results; hence the null hypothesis is accepted. It can be seen from this table that for the two parameters p-value is much greater than 0.05 and t stat is less than t critical (two tail). Hence owing to these, the null hypothesis which states that there is no significant difference between the corresponding results is accepted for the two parameters considered.

**Table 4: Summary of t test for theoretical results against ANN predicted results**

S/N	Parameter	t stat	t critical (two-tail)	P (two tail)	$\alpha$	Comment	
1.	BMEP	0.1083186	1.9627654	0.9137685	0.05	No difference	Significant
2.	Thermal Efficiency	0.0214411	1.9627654	0.9828987	0.05	No difference	Significant

**t test for ANN and Experimental Results**

Table 4.4 shows the summary of t test results obtained when ANN predicted results are compared with their corresponding experimental results. It can be seen from this table that for BSFC, t stat is -0.0084741 which is less than t critical (two tail) value of 1.9627654 and p (two tail) value of 0.9932406 is much greater than 0.05 significant level hence, the null hypothesis is accepted. For BP, p (two tail) value of 0.9382252 is greater than 0.05, this indicates that there is no significant difference between the two sets of results. EGT has t stat value of 0.1798377 which is less than t critical (two tail) value of 1.9627687 hence, the null hypothesis is accepted. Considering the table, it could be deduced that, at the overall the null hypothesis is accepted for all the three parameters considered.

**Development of predictive models for the selected engine performance parameters using Design Expert Software****Response 1: BMEP**

In order to describe the variation of this response, BMEP with independent variables and to test for its adequacy, the design programme suggested a quadratic model. The Model F-value of 1058.79 means the model is significant (Table 4.5). There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise (Oladapo and Akanbi, 2015; Onawumi *et al.*, 2016). Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, B, C, B<sup>2</sup>, C<sup>2</sup> are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve the model. The "Pred R-Squared" of 0.9951 is in reasonable agreement with the "Adj R-Squared" of 0.9973 (Table 4.6). The ratio of 123.748 indicates an adequate signal. This model can be used to navigate the design space (Aremu *et al.*, 2014; Onawumi *et al.*, 2016).

**Table 5: Summary of t test for experimental results against ANN predicted results**

S/N	Parameter	t stat	t critical two-tail	P (two tail)	$\alpha$	Comment	
1.	BSFC	-0.0084741	1.9627654	0.9932406	0.05	No difference	Significant
2.	BP	0.0775236	1.9627654	0.9382252	0.05	No difference	Significant
3.	EGT	0.1798377	1.9627687	0.8573229	0.05	No difference	Significant

**Table 6: ANOVA for response surface quadratic model (BMEP)**

Source	Sum of Squares	DF	Mean Square	F-Value	Prob > F	
<b>Model</b>	1.106E+005	<b>9</b>	12289.60	1058.79	< 0.0001	Significant
A	56101.33	1	56101.33	4833.33	< 0.0001	
B	143.37	1	143.37	12.35	0.0027	
C	36946.68	1	36946.68	3183.09	< 0.0001	
A <sup>2</sup>	17.45	1	17.45	1.50	0.2368	
B <sup>2</sup>	16051.13	1	16051.13	1382.86	< 0.0001	
C <sup>2</sup>	1325.12	1	1325.12	114.16	< 0.0001	
AB	9.36	1	9.36	0.81	0.3816	
AC	6.90	1	6.90	0.59	0.4513	
BC	5.07	1	5.07	0.44	0.5175	
Residual	197.32	17	11.61			
Cor Total	1.108E+005	27				

Table 7: Model estimation result

Response	BMEP	Thermal Efficiency	HC Emission	CO Emission	NOx Emission
R-Squared	0.9982	0.9953	1.0000	1.0000	0.9867
Adj- R-Squared	0.9973	0.9929	1.0000	1.0000	0.9796
Pred R-Squared	0.9951	0.9867	1.0000	1.0000	0.9692
Adeq Precision	123.748	78.751	1449.729	3499.902	42.610
Std. Dev.	3.41	0.61	0.72	1.44	4.66
Mean	219.91	34.17	579.14	2236.11	222.29
C.V.	1.55	1.79	0.12	0.064	2.10
PRESS	544.45	18.12	23.78	68.69	853.23

Other responses were further analysed following the same processes and the results are as presented in Tables 6 and 7.

#### Presentation of model equations for performance characteristics

All the model equations are given in terms of coded factors and the input parameters are as stated below for all the equations;

A = Load (%),

B = Speed (rpm),

C = Equivalent ratio and

E = Exponential function

#### Response 1: BMEP (kPa)

$$\text{BMEP} = +245.62 + 55.83*A + 2.82*B + 45.31*C - 1.71*A^2 - 51.72 *B^2 + 14.86* C^2 + 0.88*A*B + 0.76*A*C - 0.65*B*C$$

#### Response 2: Thermal Efficiency (%)

The model equation is given as:

$$\text{Thermal Efficiency} = +40.26 - 2.82*A + 2.18*B - 6.36*C + 0.53*A^2 - 7.80*B^2 - 1.87*C^2 + 0.47*A*B + 0.58 *A*C + 0.46*B*C$$

Table 8: Design data for performance parameters

Study Methodology: Response Surface		Experiments:27 Blocks: No Block				
Initial Design: Historical Data						
Design Model: Quadratic						
Response Name	Minimum	Maximum	Unit	Trans	Model	
1 BMEP	101.6	357.0	kPa	None	Quadratic	
2 Thermal Efficiency	19.5	48.5	%	None	Quadratic	

## V. Conclusion

This study investigated the effects of three operating parameters on two performance parameters of SI engines using theoretical, experimental and ANN methods. The following conclusions can be drawn based on the various results obtained in this work;

- Engine speed of 3000rpm gave the peak value for most of the SI engine parameters investigated in this study and these values decreased before and after this speed.
- All of the SI engine parameters investigated in this work except thermal efficiency increased with increase in engine load with highest value obtained at maximum load of 100%.

## Recommendations

The following recommendations are made for further studies;

- Compression ignition, CI engines should be investigated using the same methods.
- The performance parameters investigated should be increased to include gas exchange processes, cooling system and lubricating system.
- The effect of heat transfer on thermal efficiency of SI engines should be investigated.

## REFERENCES

- [1]. Aremu M. O., Oke E. O., Arinkoola A. O. and Salam K. K. (2014) ‘Development of Optimum Operating Parameters for Bioelectricity Generation from Sugar Wastewater Using Response Surface Methodology’ Journal of Scientific Research & Reports 3(15): 2098-2109, 2014; Article no. JSRR.2014.15.009
- [2]. Ayeb M., Lichenthäler D., Winsel T., Theuerkauf H. J., (1998) SI Engine Modeling Using Neural Network, *SAE Paper n. 980790, - SP-1357 pp. 107-115.*
- [3]. Bang-Quan H., Jian-Xin W., Ji-Ming H., Xiao-Guang Y. and Jian-Hua X., (2002). A study on emission characteristics of an EFI engine with ethanol blended gasoline fuels. 941867. Atmospheric Environment, [www.elsevier.com/locate/atmosenv](http://www.elsevier.com/locate/atmosenv) p 949–957
- [4]. Barhm-Ab-Mohamad (2013) A simulate model for analyzing the effect of engine Design parameters on the performance and emissions of Spark ignition engines
- [5]. Baumann B. M., (1997) Intelligent Control Strategies for Hybrid Vehicles Using Neural Networks and Fuzzy Logic, Master Thesis, The Ohio State University,.
- [6]. Charles, F. T., (2011) The Internal-combustion Engine. Books.google.co.in. 1985-01-01. ISBN 9780262700276. Retrieved 22/10/2011
- [7]. Cirean, D. C., Meier, U. Masci, J., Schmidhuber J., (2012) Multi-Column Deep Neural Network for Traffic Sign Classification. Neural Networks
- [8]. De, J. N., Vianna, S., Do, A., Reis, V., De, A. B., Oliveira, S., Fraga, A. G. and De Sousa, M. T., (2005) Reduction of Pollutants Emissions on SI Engines - Accomplishments With Efficiency Increase. Journal of the Braz. Soc. of Mechanical Science & Engineering Vol. 27, No. 3: 217-222
- [9]. Elijah I. and Asere A., (2008) A Comparative Performance and Exhaust Analysis of Blended Groundnut Oil and Mineral Oil Based Lubricant Using Spark Ignition Engine. Cigre Journal Manuscript EE07017volx.
- [10]. Farley, B. G., and Clark W.A., (1954) "Simulation of Self-Organizing Systems by Digital Computer". IRE Transactions on Information Theory (4): 76–84. doi:10.1109/TIT.1954.1057468.
- [11]. Frenklach, M., Packard, A., Seiler P. and Feeley R., (2004) Collaborative data processing in developing predictive models of complex reaction systems. International Journal of Chemical Kinetics, 36(1):57-66, doi: 10.1002/kin.10172.
- [12]. Gosai D. C. and Nagarsheth H. J., (2014) Performance and Exhaust Emission Studies of an Adiabatic Engine with Optimum Cooling, 2nd International Conference on Innovations in Automation and Mechatronics Engineering, ICIAME.
- [13]. Graves, A., Liwicki, M., Fernandez, S., Bertolami, R., Bunke, H. and Schmidhuber.J., (2009) A Novel Connectionist System for Improved Unconstrained Handwriting Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 5,
- [14]. Hashemi S. H., Fard D., Almassi, M., Borghei, A. M. and Beheshti B. (2013) Simulation of Small Diesel Engine Vibration using Artificial Neural Network International Journal of Agriculture and Crop Sciences. IJACS/2013/5-18/2084-2090 ISSN 2227-670X ©2013 IJACS Journal Hecht-Nielsen R., (1987) Neurocomputing, Addison-Wesley.
- [15]. Hinton, G. E., Osindero, S. and Teh, Y. W., (2006). "A Fast Learning Algorithm for Deep Belief Nets". Neural Computation 18 (7): 1527–554.:10.1162/neco.2006.18.7.1527. PMID 16764513.Edit
- [16]. Holzmann H., Halfmann Ch., Isermann R., NeuroFuzzy (1998) Modeling of Automotive SI- Engine Characteristics, in proc. of IFAC Symposium Advances in Automotive Control 98, Mohican State Park, Loudonville, OH, USA, February 26 - March 1, pp. 156-160. International Journal of Mechanical Engineering and Technology (IJMET) volume 4, issue 5, September - October (2013) © iaeme issn 0976 – 6340 (print), ISSN 0976 – 6359
- [17]. Jadhao, J. S. and Thombare, D. G., (2013) Review on Exhaust Gas Heat Recovery for I.C. Engine. International Journal of Engineering and Innovative Technology (IJEIT) Volume 2, Issue 12: 93-100. ISSN: 2277-3754; ISO 9001:2008 Certified
- [18]. Jeffrey J. G. and Elliott N. G., (1993) Gasoline composition effects in a range of European vehicle technologies. SAE Technical Paper Series 932680.
- [19]. Johan, W., (2003) “Dynamics study of Automobile Exhaust System.”Department of Mechanical Engineering, Blekinge Institute of Technology, Sweden, Pg 1 - 45.
- [20]. John M., (2012). "Scientists See Promise in Deep-Learning Programs". NewYork Times. November 23, Keshav S. V. (2012) Control of Exhaust Emissions from Small Engines Using E-10 and E-85
- [21]. Fuels Department of Mechanical Engineering University of Michigan- Dearborn Dearborn, Michigan 48128
- [22]. Kraft M. and Mosbach S., (2009) The future of computational modelling in reaction engineering Technical Report 84, c4e-Preprint Series, Cambridge.
- [23]. Lange, W. W., Muller, A., McArragher, J. S., and Schafer, V., (1994) The effect of gasoline composition on exhaust emissions from modern BMW vehicles. SAE Technical Paper Series
- [24]. Manieniyani, V. and Sivaprakasam, S., (2013) Experimental Analysis of Exhaust Gas Recirculation on DI Diesel Engine Operating with Biodiesel. International Journal of Engineering and Technology Volume 3 No. 2: 129-135 ISSN: 2049-3444 © 2013 – IJET Publications UK.
- [25]. McCulloch, W. and Walter P., (1943) "A Logical Calculus of Ideas Immanent in Nervous Activity". Bulletin of Mathematical Biophysics 5 (4): 115-133. doi:10.1007/BF02478259
- [26]. McDonald, C. R., Shore, P. R., Lee, G. R., den Otten, J. and Humphries, D. T., (1994) The effect of gasoline composition on stoichiometry and exhaust emissions. SAE Technical Paper Series 941868.
- [27]. Neimark, A., Kholmer, V. and Sher, E., (1994) The effect of oxygenates in motor fuel blends on the reduction of exhaust gas toxicity. SAE Technical Paper Series 940311.
- [28]. Neural Information Processing Systems (NIPS) Foundation, (2009) pp. 545–552
- [29]. Oladapo S. O. and Akanbi O. G. (2015). Models for predicting body dimensions needed for furniture design of junior secondary school one to two students. The International Journal of Engineering and Science (IJES) Volume 4 Issue 4 PP.23-36 ISSN (e): 2319 – 1813ISSN (p): 2319 – 1805
- [30]. Onawumi A. S, Adebisi K. A., Fajobi M. O. and Oke, E. O. (2016) ‘Development of Predictive Models for Some Anthropometric Dimensions of Nigerian Occupational Bus Operators’ European International Journal of Science and Technology ISSN: 2304-9693 [www.ejst.org.uk](http://www.ejst.org.uk)
- [31]. Ortmann S., Glesner M., Rychetsky M., Tubetti P., Morra G., (2000) Engine Knock Estimation Using Neural Networks based on a Real-World Database, SAE Paper n. 980513, SP-1357, pp. 17-31.
- [32]. Patterson D. W., (1995) Artificial Neural Networks – Theory and Applications, Prentice Hall, Paykani A., Khoshbakhti R. and Shervani. M. T., (2011) “Experimental and numerical study of venturi EGR system in a dual fuel engine”, International Conference on Advanced Research and Applications in Mechanical Engineering, Lebanon.



- [33]. Rajput R. K., (2011) A Text Book of Automobile Engineering – R.K. Rajput – Google Books.
- [34]. Books.google.co.in. 2007-01-01. ISBN 9788170089919. Retrieved 2011-10-22.
- [35]. Rajput, R. K., (2006) Thermal Engineering, Sixth edition, Laxmi Publications (P) LTD New Delhi, India. 1018-1171
- [36]. Renhua F., Jing Y., Daming Z., Banglin D., Jianqin F., Jingping L. and Xiaoqiang L., (2013).
- [37]. Experimental study on SI engine fuelled with butanol–gasoline blend and H<sub>2</sub>O addition Energy Conversion and Management journal homepage: [www.elsevier.com/locate/enconman](http://www.elsevier.com/locate/enconman)
- [38]. Rochester, N., Holland, J. H., Habit, L. H. and Duda W. L., (1956) "Tests on a cell assembly theory of the action of the brain, using a large digital computer". IRE Transactions on Information Theory 2 (3): 80–93.  
doi:10.1109/TIT.1956.1056810.<http://www.psych.utoronto.ca/users/reingold/courses/ai/cache/neural3.html>
- [39]. Ronald, D. M., (2006) Internal combustion engines. Mechanical Engineers' Handbook: Energy and Power, Volume 4, Third Edition. John Wiley & Sons, Inc.; Edited by Myer Kutz: 886-921.
- [40]. Saravanan N. and Nagarajan G., (2008) "An experimental investigation on performance and emissions study with port injection using diesel as an ignition source for different EGR flow rates", International Journal of Hydrogen Energy, 33: 4456-4462.(1)
- [41]. Shivakumar, Srinivas P. P., ShrinivasaRao B. R. and Samaga B. S. (2010), performance and emission characteristics of a 4 stroke c.i. engine operated on honge methyl ester using artificial neural network ARP Journal of Engineering and Applied Sciences Vol. 5, no. 6, June ISSN 1819-6608 ©2006-2010 Asian Research Publishing Network (ARP).
- [42]. Suvendu M. and Om Prakash, (2013) Analysis Of Exhaust Emission Of Internal Combustion Engine Using Biodiesel Blend International Journal of Emerging Technology and Advanced Engineering Website: [www.ijetae.com](http://www.ijetae.com) (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 5, May)
- [43]. Venkatasubramanian V., (2009) Drowning in data: Informatics and modeling challenges in a data rich networked world. AIChE Journal, 55(1):2-8, 2009. doi: 10.1002/aic. 11756.
- [44]. Wallington, T. J., Kaiser, E. W. and Farrell, J. T. (2006) Automotive Fuels and Internal Combustion Engines: A Chemical Perspective. Chemical Society Review, 35:335–347. [www.rsc.org/csr](http://www.rsc.org/csr)

ADIO, T. A, et. al. "Parameter Evaluation of Spark Ignition Engine Using Artificial Neural Network." *American Journal of Engineering Research (AJER)*, vol. 9(06), 2020, pp. 120-136.