Prediction of Ethanol-Gasoline Blend Fuelled Spark Ignition Engine Performance using Dimensional Analysis

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Abstract:

Ethanol is blended with pure gasoline for use as a fuel in a gasoline engine. It is required to conduct physical tests on engines to observe the engine performance for these fuel blends. However, mathematical equations provide a quick, effective and accurate alternate for physical tests. It may not be possible to develop the mathematical relations for the specific operating conditions of engine and fuel. It is possible to use dimensional analysis approach to develop mathematical model. Dimensional analysis approach is used in this research work for deriving the mathematical correlations of Indicated Mean Effective Pressure, Brake Power, Indicated Power and Brake Specific Fuel Consumption as engine performance parameters. Their relations are established with engine speed, load on engine, calorific value of fuel fractions and clearance volume of engine as independent parameters. Buckingham π theorem is used for formulating the relations having proportionality sign showing the possible relations of each dependent parameter with all four independent parameters. Regression analysis is used for eliminating proportionality signs from the equations developed. Mathematical relations developed by the dimensional analysis are accurate. Root Mean Square errors have noted a minimum of 4.19 for Brake Specific Fuel Consumption and a maximum 8.56 for Brake Power. The average percentage errors are less than 1%.

Keywords: Dimensional Analysis, Buckingham π Theorem, Engine Performance, Engine Performance Prediction Model, Regression Analysis, Alternative Fuel

1. Introduction:

Fossil fuel use is increasing every day for various applications including generation of power and automobile applications. The requirement of alternative fuels is increasing due to stringent emission norms and depleting fossil fuels. Ethanol as an alternative fuel, blended in gasoline, gives enhanced engine performance in terms of torque, power and brake thermal efficiency (Hatte & Bhalerao, 2019). Adding the ethanol in gasoline improves the combustion parameters and engine performance in terms of brake power, brake thermal efficiency and specific fuel consumption. (Efemwenkiekie et al, 2019). Ethanol addition in gasoline also increases the octane number of the fuel blends and reduces the harmful emissions from the engine. (Mortadha et al, 2021) Ethanol is also added in diesel fuel and used as fuel blend as an alternative to conventional fuels. (Limin et al, 2021) For each fuel fraction and at different operating conditions, it is essential to physically carry tests on the engine to find the engine performance. To save the time and costs, it is beneficial to develop a mathematical model for engine performance prediction.

The effects of blending ethanol with gasoline on engine performance and emission are observed using Quasi-dimensional models. (Duc-Khanh et al, 2018; Mantilla et al, 2010). Mathematical models have developed for predicting the cylinder pressure, ignition delay, exhaust emissions, research octane number and flame propagation (Sivalingam, et al, 2015). Multivariable models for predicting specific parameters like Reid Vapour Pressure, Octane Number are also developed (Oduola and Iyaomolere, 2015). These mathematical models are based on the fixed inter-relations of engine parameters and can not be formulated in terms of any customised operating parameters.

Artificial Neural Network (ANN) technique is also used to predict the engine performance and exhaust emissions (Gongpinget al, 2019; Gul,et al, 2019). ANN predicted the performance of the engine with R values above 0.99 and high accuracy of 99%.

In physical science and engineering applications, Dimensional Analysis (DA) is a fundamental method which analytically reduces the number of experimental variables affecting a given phenomenon before conduction of experimentation (Mark et al, 2013). Dimensional analysis approach is successfully used for prediction of engine performance using Buckingham π Theorem (Patil et al, 2020). DA has distinct advantages of reducing number of causal factors and establishing the relations among the generated variables. It also provides the possibility of scalability of the results (Weijie et al, 2014). DA is used for transforming the variables with dimensions to dimensionless variables. It is also seen that dimensionless variables are better fit in statistical modelling (Weijie & Dennis, 2017).

DA is very effective in cases, where mathematical models are either unknown or can not be effectively solved (Matthias, 2016; Price,2003). Flaga (2015) also explained the procedure and fundamentals of DA. He explained the Buckingham π principle and the process of using the same. Dhaundiyal (2014) used Buckingham π theorem for prediction of Brake Thermal Efficiency (BTE) of the engine using 16 variables for prediction of BTE.

Prediction equations for performance of CI engine were formulated by Dheeraj et al (2017) using five variables. Development of experimental data-based model using DA approach was developed by Deshmukh et al (2019).

In the present study, DA tool is used for predicting the engine performance effectively in terms of Indicated Mean Effective Pressure, Brake Power, Indicated Power and Brake Specific Fuel Consumption. This is done using Buckingham's π theorem using the experimental data of engine testing observed for Engine Speed, Load, Calorific Value and Clearance Volume. It has resulted in reduction of the time and energy required for actual engine test, using various fuel fraction of ethanol and gasoline. The approach of using DA, its process, use and effectiveness is presented in this paper. Engine is tested at different ethanol-gasoline fuel fractions from E0 to E40 and compression ratio from 7 to 10 for various engine speeds from 1300 to 1700 rpm. This research work does not include any combustion reactions and is based on macroscopic approach.

2. Dimensional Analysis:

Dimensional analysis is a proven process used to find the relationship among variables of any system. This approach is widely used in fluid mechanics and heat transfer systems. It helps in finding out the possible relationships among physical quantities in complicated systems by their dimensions.

Buckingham's π theorem shows that physical equations must be dimensionally homogeneous. It also means that any meaningful equations and inequalities must have the same dimensions in the left and right sides of the equation (Deshmukh et al, 2013). This theorem is used in this paper to establish the possible relationship among the independent and dependent variables.

Four dependent variables Indicated Mean Effective Pressure (IMEP), Brake Power (BP), Indicated Power (IP) and Brake Specific Fuel Consumption (BSFC) are considered for finding the possible relations with four independent variables Engine Speed, Load, Calorific Value and Clearance Volume. All variables, their units, and dimensions are shown in Table 1.

Table 1 List of variables for dimensional analysis

Sr No	Type of variable	Variable	Unit	Dimension
1	Dependent	IMEP (P_m)	Bar	$\frac{M}{LT^2}$
2	Dependent	BP	kW	$\frac{ML^2}{T^3}$
3	Dependent	IP	kW	$\frac{ML^2}{T^3}$
4	Dependent	BSFC	Kg/kWh	$\frac{T^3}{L^3}$
5	Independent	Engine Speed	Rev/Minute	$\frac{1}{T}$
6	Independent	Load	N	$\frac{ML}{T^2}$
7	Independent	Calorific Value	kW/Kg	$\frac{L^2}{T^2}$
8	Independent	Clearance Volume	m^3	L^3

Consider IMEP (P_m) as the first dependent variable and Engine Speed (N), Load (F), Calorific Value (Cv) and Clearance Volume (Vc) as independent variables. Clearance volume is taken as an independent variable as a representative variable for compression ratio, as compression ratio does not have dimension.

Total no. of variables = $n = 5$

No. of fundamental Dimensions = $m = 3$

Total No. of π Terms = $n - m = 5 - 3 = 2$

Each π term will have = $m + 1 = 4$

Repeating Variables = $m = 3$

IMEP $= f(N, F, C_v, V_c)$

$\pi_1 = [N]^{a_1} [F]^{b_1} [C_v]^{c_1} P_m$

$\pi_2 = [N]^{a_2}[F]^{b_2}[C_v]^{c_2} \mathrm{v}_c$

$\pi_1 = M^0 L^0 T^0 = \left[\frac{1}{T}\right]^{a_1} \left[\frac{ML}{T^2}\right]^{b_1} \left[\frac{L^2}{T^2}\right]^{C_1} \frac{M}{LT^2}$

Power of M –

$0 = b_1 + 1$

$\therefore b_1 = -1$

Power of L –

$0 = 2c_1 + b_1 - 1$

$0 = 2c_1 - 1 - 1$

$0 = 2c_1 - 2$

$2c_1 = 2$

$c_1 = 1$

Power of T –

$0 = -a_1 - 2b_1 - 2c_1 - 2$

$0 = -a_1 + 2 - 2 - 2$

$a_1 = -2$

$\pi_2 = M^0 L^0 T^0 = \left[\frac{1}{T}\right]^{a_2} \left[\frac{ML}{T^2}\right]^{b_2} \left[\frac{L^2}{T^2}\right]^{c_2} L^3$

Power of M –

$0 = b_2$

Power of L –

$0 = b_2 + 2c_2 + 3$

$2c_2 = -3$

$c_2 = -{}^{3}\!/_{2}$

Power of T –

$0 = -a_2 - b_2 - c_2$

$0 = -a_2 - 0 + \frac{3}{2}$

$a_2 = {}^{3}\!/_{2}$

$\therefore \pi_1 = [N]^{-2} [F]^{-1} [C_v]^{1} P_m$

Rearranging the terms,

$$\therefore \pi_1 = \frac{P_m C_v}{FN^2}$$

$$\pi_2 = [N]^{3/2}[F]^0 \, [C_v]^{3/2} \, V_c$$

Rearranging the terms, $\pi_2 = \frac{V_c N^{3/2}}{C_v{}^{3/2}}$

$$f\,(\pi_1, \pi_2) = 0$$

$$f\left(\frac{P_m C_v}{FN^2}\ , \frac{V_c N^{3/2}}{C_v{}^{3/2}}\right) = 0$$

$$\frac{P_m C_v}{FN^2} = \emptyset \left(\frac{V_c N^{3/2}}{[C_v]^{3/2}}\right)$$

Or

$$P_m = \frac{FN^2}{C_v} \, \emptyset \left(\frac{V_c N^{3/2}}{[C_v]^{3/2}}\right) \qquad (1)$$

A similar exercise is done for other dependent parameters to find possible relations. For next dependent parameter Brake Power,

$$BP = F(N, F, C_v, V_c)$$

$$\pi_1 = [N]^{a_1} \, [F]^{b_1} \, [C_v]^{c_1} \, BP$$

$$\pi_2 = [N]^{a_2} [F]^{b_2} \, [C_v]^{c_2} \, \mathrm{v}_c$$

Final relationship will lead to

$$BP = F\sqrt{C_v} \, \emptyset \left(\frac{NV_c}{C_v{}^{3/2}}\right) \qquad (2)$$

Similarly, dimensional analysis is done for BSFC and relationship equation is established as

$$BSFC = C_v{}^{3/2} \, \emptyset \, \frac{N^3 V_c}{C_v{}^{3/2}} \qquad (3)$$

After dimensional analysis, the relation equation for IP is given as

$$IP = F\sqrt{C_v} \, \emptyset \left(\frac{NV_c}{C_v{}^{3/2}}\right) \qquad (4)$$

3. Experimentation:

The setup for experimentation has Variable Compression Ratio (VCR) engine having a facility of changing the compression ratio (CR) in the range of 7 to 10. It is a single cylinder Kirloskar make diesel engine modified as a research engine. It is also a multi-fuel engine which can run on various fuels. Engine is loaded using eddy current dynamometer. This helps in accurate and fine loading of the engine.

Fig 1: Experimental Setup for Engine Testing.

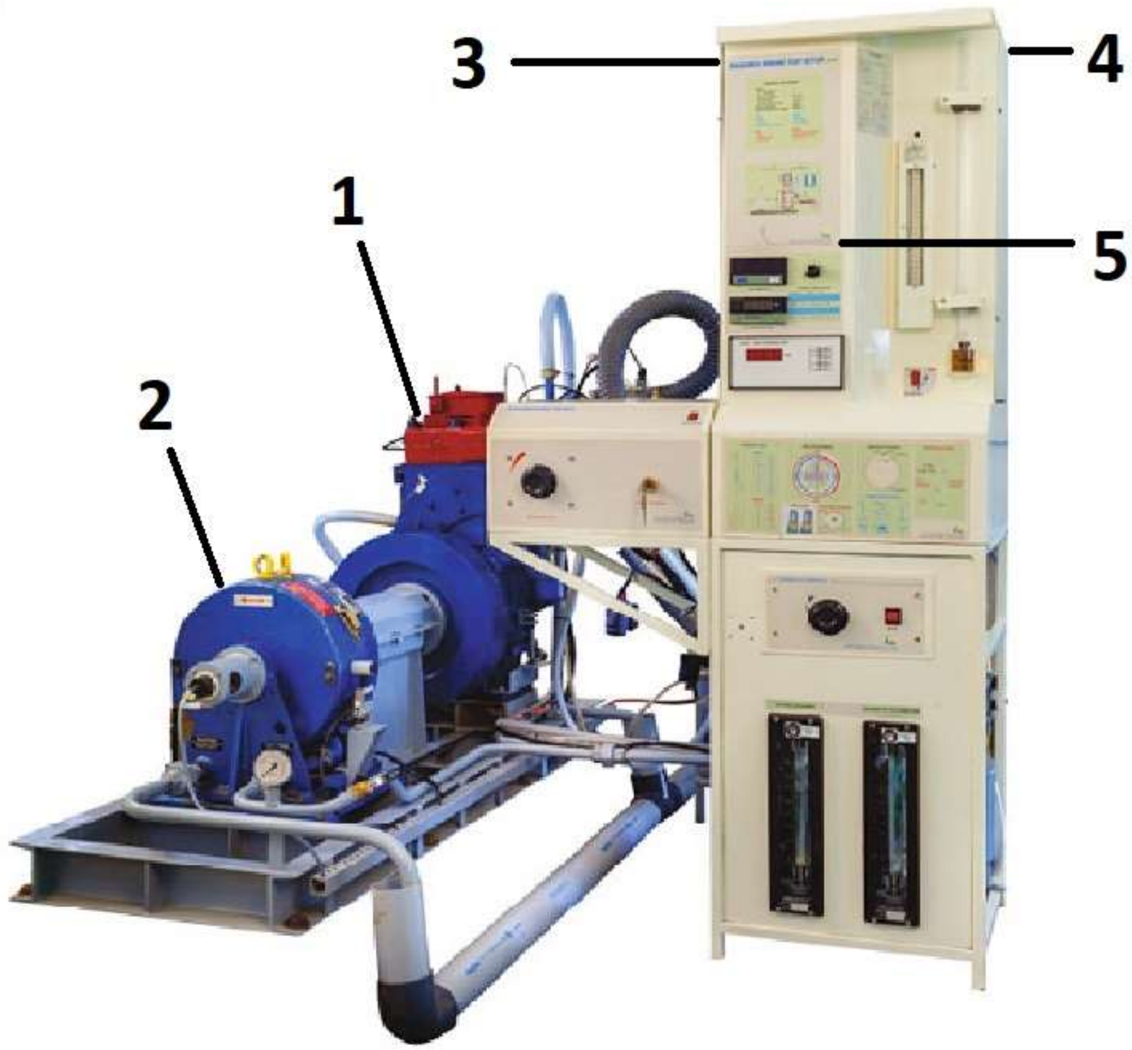


Fig 2: Engine Experimental Setup

Fig 3: Control Panel

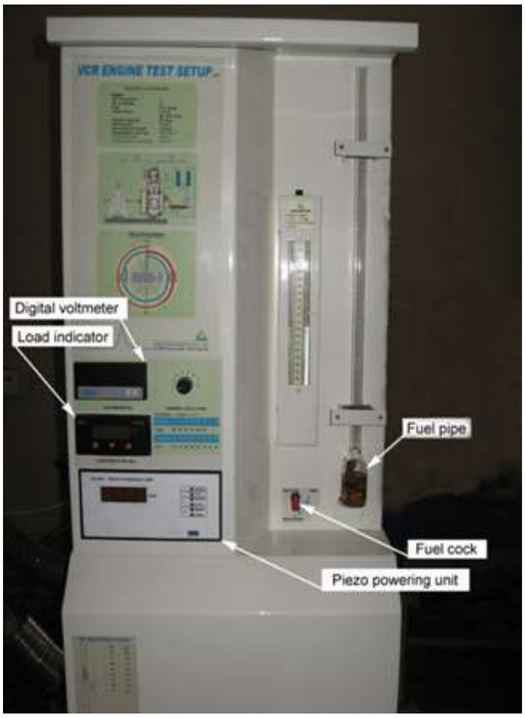
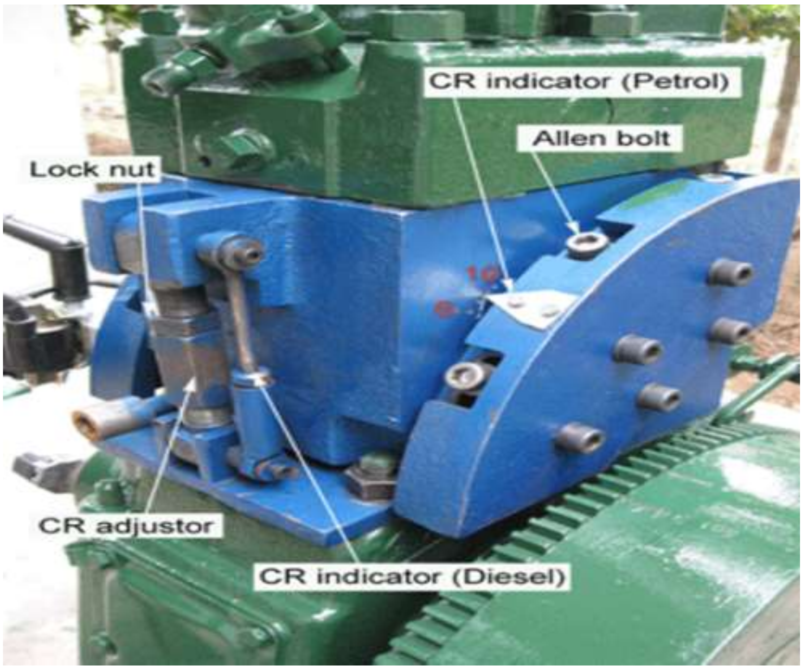


Fig 4: Compression Ratio Adjustment Assembly



The experimental test setup is shown in Fig. 1. Engine 1 is connected to Eddy Current Dynamometer 2 for loading the engine. Two fuel tanks 3 and 4 are provided to supply two different fuels to the engine. Tank 3 supplies pure gasoline, while tank 4 supplies blends of ethanol and gasoline. Panel 5 has controllers for engine loading, throttle, water flow control etc. The exhaust gas calorimeter is used for finding the heat losses to exhaust gases. After the calorimeter, exhaust gases are tapped in an exhaust gas analyser for measurement of exhaust gas contents.

Detailed pictorial view of the experimental setup is shown in Fig 2. This set-up of experimentation has a panel box, engine, dynamometer, exhaust gas calorimeter, provision for exhaust gas emission measurement, continuous water flow etc. Panel, as shown in Fig 3, is fitted with two fuel tanks, air box, fuel flow measuring unit, manometer for air flow measurement, transmitters for air and fuel flow rate measurement, hardware interface and various indicators. Indicators are provided for load and speed. Fuel measurements can be done manually using a fuel cock and a fuel indicator.

Compression ratio of the engine can be adjusted using a tilting cylinder arrangement as shown in Fig 4. CR adjustor stud is used to tilt the engine cylinder, even in running condition of the engine. Lock nut is used for locking the position of the stud. Two indicators of CR are provided. One each is used for diesel and petrol mode of the engine. Six allen bolts are provided, three on each side of cylinder, for locking the cylinder after changing the CR.

All the readings are recorded after initial idle running the engine for 20 minutes and ensuring the steady state condition of the engine. The first test is carried out with pure gasoline fuel.

Various fuel fractions of ethanol and gasoline are used for preparing fuel blends. 10 % ethanol mixed with 90% gasoline by volume is treated as E10. Similarly, blends are prepared for E20, E30 and E40. All the readings are recorded by keeping the throttle in widely open condition.

Engine is loaded by eddy current dynamometer. Initially the speed of the engine is maintained to its highest rated speed and gradually the load on the engine is increased for reducing the speed of the engine. Readings are taken from 1700 rpm to 1300 rpm in an interval of 100 rpm. For each single fuel fraction, engine's compression ratio is also changed from 7 to 10 at the interval of 1. Performance of the engine is observed for each fuel fraction with change in compression ratio and speed of the engine.

Engine-Soft software is used for collecting the data from sensors. This software compiles the information and generates the data in Microsoft word format. Regression analysis is done on the readings recorded.

4. Regression Analysis:

Regression analysis is done on the data of experimental observations of independent variables. It is done for simplification of Equations 1,2,3 and 4. These equations are used below for establishing the relations of dependent variables with independent variables.

In Eq. 1, for simplification purpose, consider

$A = \frac{FN^2}{C_v}$ and $B = \frac{V_c N^{3/2}}{[C_v]^{3/2}}$

Eq. 1 is simplified as

$$P_m = A \emptyset B \quad (5)$$

Regression tool is used in Minitab 17 to fit the regression model. Minitab 17 provides the solution to use various tools for statistical analysis. Regression tool is used for finding the relationship of P_m with A & B of Eq. 5.

$$P_m = 0.006284A + 1180B \quad (6)$$

Eq. 6 gives the regression equation in terms of A & B. Substituting the values of A and B in Eq. 6 results in

$$P_m = 0.006284\frac{FN^2}{C_v} + 1180\frac{V_c N^{3/2}}{[C_v]^{3/2}} \quad (7)$$

Eq. 7 establishes the relationship of independent variables with the dependent variable P_m.

In Eq. 2, for simplification purpose consider

$A = F\sqrt{C_v}$ and $B = \frac{NV_c}{C_v^{3/2}}$

Eq. 2 is simplified as

$$BP = A \emptyset B$$

After using regression tool in Minitab 17, for fitting the regression model, BP is found as

$$BP = 0.01108A + 30283B \quad (8)$$

Eq. 8 gives the relationship of BP with A and B.
Substituting the values of A and B in Eq. 8 results in

$$BP = 0.001108F\sqrt{C_v} + 30283\frac{NV_c}{{C_v}^{3/2}} \tag{9}$$

In similar lines, from Eq. 3, regression equation for BSFC is found as

$$BSFC = 0.0A + 0.002338B \tag{10}$$

Eq. 10 gives the relationship of BSFC with A and B.

Where

$A = {C_v}^{3/2}$ and $B = \frac{N^3V_c}{{C_v}^{3/2}}$

Substituting the values of A & B above in Eq. 10 gives,

$$BSFC = 0.002338\frac{N^3V_c}{{C_v}^{3/2}} \tag{11}$$

The final equation for BSFC is given in Eq. 11

In Eq. 4, for simplification purpose consider

$A = F\sqrt{C_v}$ and $B = \frac{NV_c}{{C_v}^{3/2}}$

Eq. 4 is simplified as

$IP = A \emptyset B$

Using Minitab 17, regression equation is found as

$$IP = 0.00991A + 83146B \tag{12}$$

Substituting the values of A and B in Eq. 12 results in

$$IP = 0.00991F\sqrt{C_v} + 83146\frac{NV_c}{{C_v}^{3/2}} \tag{13}$$

Eq. 7, 9, 11 and 13 provide the final relationships of each dependent parameters IMEP, BP, BSFC & IP respectively with the independent parameters Engine Speed, Load, Calorific Value, and Clearance Volume.

5. Results & Discussions:

DA approach provides a fast solution to derive the mathematical equations to formulate the relations between dependent and independent parameters. The equations generated by DA approach are evaluated for accuracy and usefulness. This is done at following different levels.

1. Accuracy of regression equations.

2. Validation with experimental values.

3. Comparative analysis.

5.1 Accuracy of the regression equations:

Regression analysis is used to find the exact relationship of each dependent parameter with the corresponding independent parameters.

Table 2 Model Summary

Parameter	S	R-Square, %	R-Square (Adj),%	R-Square (Predicted) %
IMEP	0.642338	98.21	98.18	98.14
BP	0.262421	99.29	99.27	99.26
BSFC	0.041188	98.67	98.64	98.62
IP	0.329043	99.33	99.31	99.30

Accuracy of regression analysis is observed from the R Square values as shown in Table 2. R square is the variation percentage mentioned in the regression model. It shows the fitness of the data in the regression model. It is expected that R square should be close to 100%. Higher values of R square ensure closeness of predicted values with actual values. It is very useful to measure the prediction accuracy of regression model. The values of R Square vary between 98.21 and 99.33. However, these values may not completely explain the predicting ability of the regression model after addition of new observations. For the best conclusion on regression model prediction accuracy, it is required to be compared with residual plots.

R square values remain same or increase with addition of new variables. It may happen even when no direct relations of newly added variable exist with output variable. R square adjusted is used for finding the change in prediction ability of the model, after possible addition of new variables. In the present work, as shown in Table 2, R square adjusted values vary between 98.18 and 99.31. It represents excellent prediction ability of the models with addition of new variables.

Predicted R-Square term is used for deciding the predicting ability of the model. In Table 2, it is observed that Predicted R-Square values are more than 98 % for all the parameters. This shows a very high value and best ability of the regression equation for prediction ability. These values of Predicted R-Square are also more helpful than adjusted R-Square for comparing models, as it is calculated with observations that may not be included in the model calculations.

S values are used to describe the response. The unit of measurement of S is the same as of response variable. It shows how close or far the data values fall with refence to fitted values. Lower S values gives better model. Table 2 gives S values within the zone of ±10 % of the variables used and gives satisfactory indicator.

Table 3 Coefficient Table

Parameter	Term	Coefficient	SE Coeff	T-Value	P-Value	VIF
IMEP	A	0.006284	0.000559	11.24	0.000	26.51

	B	1180	385	3.06	0.003	26.51
BP	A	0.001108	0.000044	24.99	0.000	13.65
	B	30283	4413	6.86	0.000	13.62
BSFC	A	0.0000	0.0000	18.55	0.000	9.30
	B	0.002338	0.000239	9.76	0.000	9.30
IP	A	0.000991	0.000056	17.82	0.000	13.65
	B	83146	5533	15.03	0.000	13.65

P values show the probability of measuring the evidence against the null hypothesis. For null hypothesis and no relation with the term and response, it is expected that P value should be close to zero and should be less than 0.05. The P value of 0.05 shows 5% probable risk in arriving at a conclusion that there exists relation when there is no actual association. Table 3 shows all the P values less than 0.05.

Fig. 5. Residual plots for IMEP

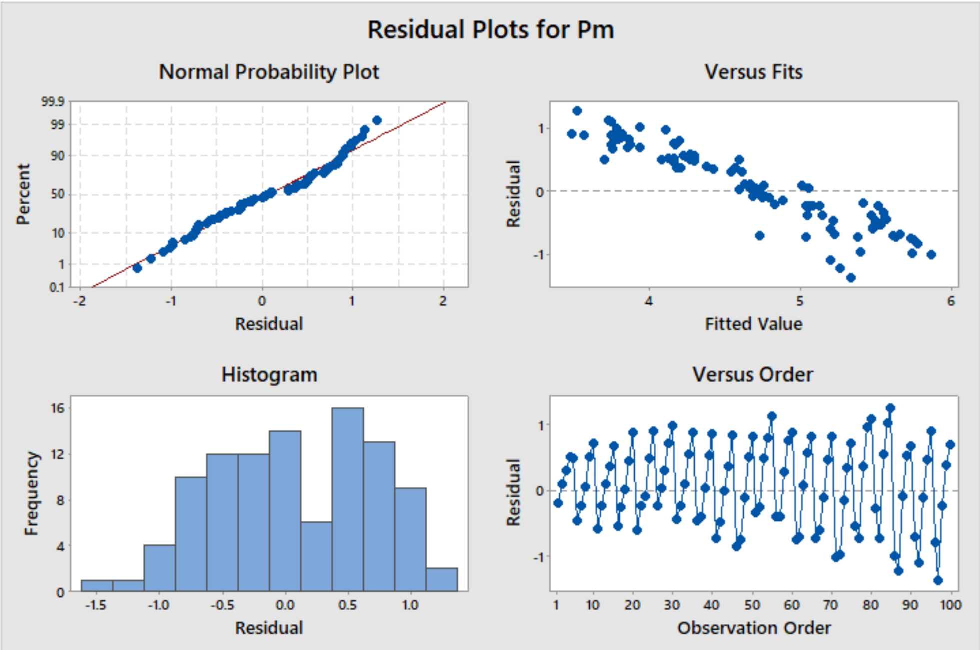


Fig. 6. Residual plots for BP

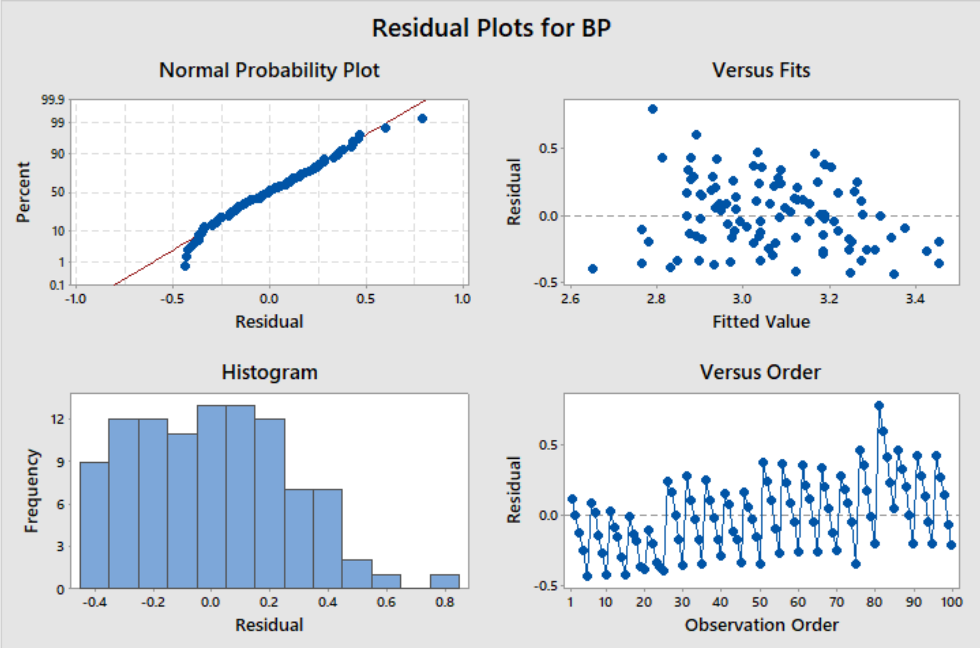


Fig. 7. Residual plots for BSFC

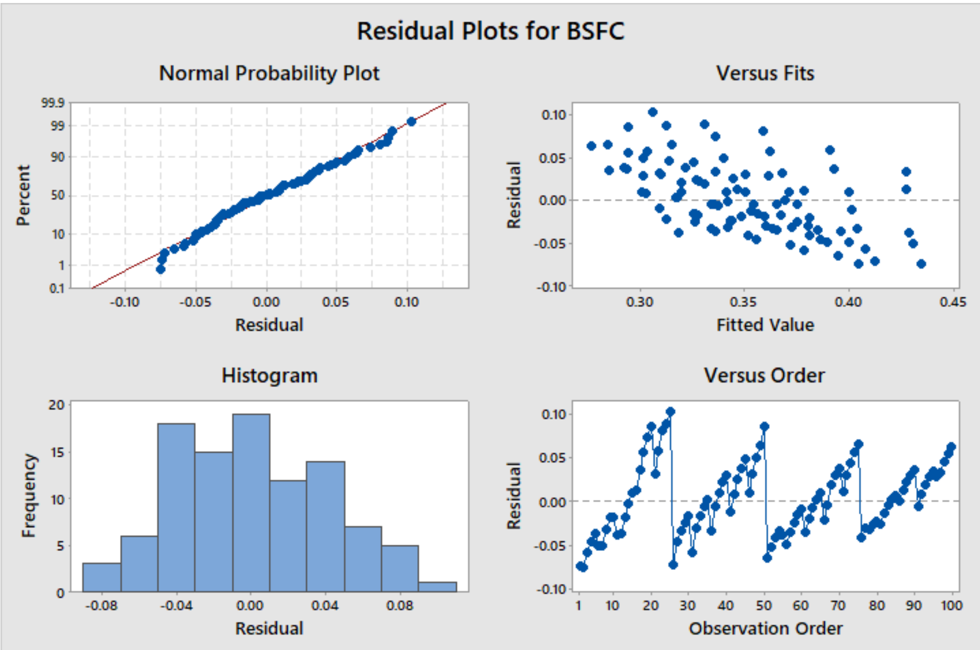
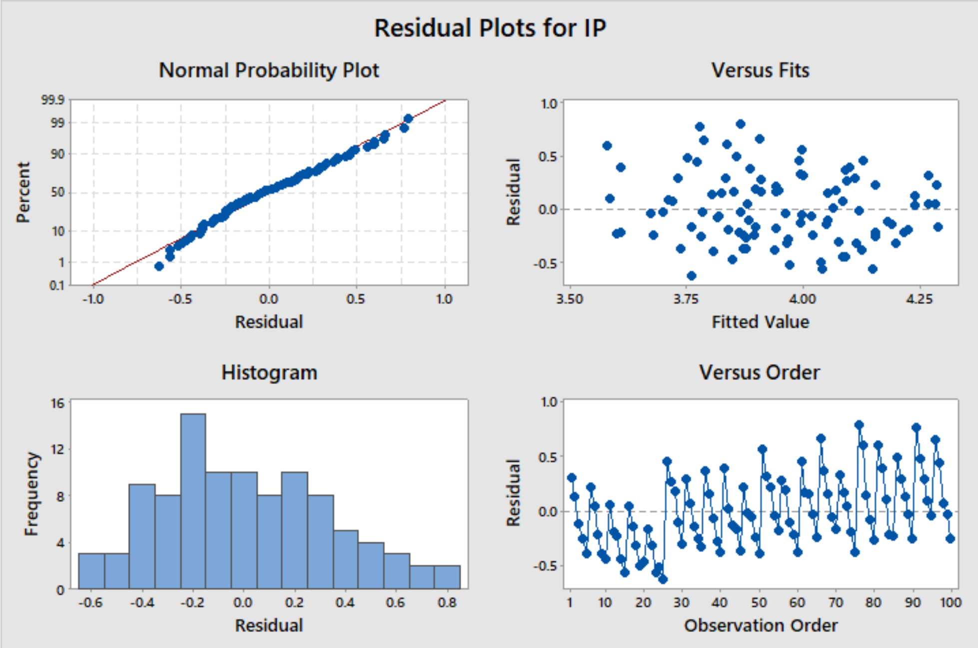


Fig. 8. Residual plots for IP



Residual plots for IMEP, BP, BSFC, and IP are shown in Fig. 5,6,7, and 8 respectively. Normal probability plots are used for verification of the assumption which resembles that residuals are distributed normally. The normal probability plots for all the parameters show that more than 95% of the residuals are normally distributed. Histograms as observed in Fig. 5,7 and 8 show that histogram bars are normally spread over the range for BP, BSFC and IP. However, the data is skewed towards left for BP as shown in Fig. 6. Versus fit plots show equal distribution of residuals on both positive and negative directions. It is also noted that there are no fixed patterns for versus fits. There is no curvilinearity for any of the versus fits and no point far away in X or Y axis. The residuals are randomly distributed and shows a good fit. Residual versus order plot are used to show the residuals in the order of data collection. For the present research work, the data is collected for 100 experiments at regular interval of speed, compression ratio and ethanol fraction in a fuel blend. The versus order plot shows this cyclic nature of data collection. This cyclic distribution versus order points for each parameter does not show any specific pattern. It is also observed that the residual data points are distributed almost equally in both the positive and negative directions.

Fig. 5,6,7 and 8 show that regression model is well fitted to predict the values of A and B. These values obtained from regression analysis are used in equations 6,8,10 and 12.

5.2 Validation with experimental values:

All the four equations developed by DA are used to predict the values of corresponding variables. These predicted values are compared with the experimental values. Error analysis is done using 100 experimental readings. The accuracy of these equations can be observed in Table 4.

Table 4 Error Table

Parameter	Average Error (Percentage)	Root Mean Square (RMS) Error
IMEP	0.257077	5.330148
BP	0.547227	8.560865
BSFC	0.172595	4.199431
IP	0.578255	8.260495

It is observed that Root Mean Square (RMS) error is minimum of 4.19 for Brake Specific Fuel Consumption and maximum 8.56 for Brake Power. Minimum average percentage error 0.172 is noted for Brake Specific Fuel Consumption and maximum 0.578 is noted for Indicated Power. This validation shows accurate prediction abilities of the mathematical equations of all the four independent variables.

5.3 Comparative Analysis:

For prediction of engine performance, mathematical equations are formulated by using the regression analysis method. Three independent parameters Calorific Value (Cv), Engine Speed (N) and Compression Ratio (CR) are used for regression analysis. The data of experiments conducted on engine for all the operating conditions is used for this regression analysis. The regression equations are given below from Eq. 14 to Eq. 17.

$$IMEP = 2.564+(6.5384\text{x}10^{-05}Cv) - (5.4049\ \text{x}10^{-05}N) + (4.7999\ \text{x}10^{-02}CR) \tag{14}$$

$$BP = -3.084+(8.3986\ \text{x}10^{-05}Cv) + (0.001N) + (0.1401CR) \tag{15}$$

$$BSFC = 0.8190 - (1.2552\ \text{x}10^{-05}Cv) + (0.0001N) - (0.01304CR) \tag{16}$$

$$IP = -1.0776+(3.8356\ \text{x}10^{-05}Cv) + (0.0022N) + (0.0114CR) \tag{17}$$

The equations generated by DA approach are compared with the regression equations. The comparison is done based on R square and R square Adjusted values. The comparative values are shown in Table 5.

Table 5 Comparative Analysis

Parameter	Dimensional Analysis Equations		Regression Analysis Equations	
	R-Square, %	R-Square (Adj),%	R-Square, %	R-Square (Adj),%
IMEP	98.21	98.18	76.1	75.3

BP	99.29	99.27	94.9	94.7
BSFC	98.67	98.64	82.8	82.2
IP	99.33	99.31	87.4	87.0

The comparative analysis shows that the values of R Square are higher for the equations generated by DA approach in comparison with the equations generated by Regression Analysis method. The same is also observed for R square Adjusted values for the DA equations. It shows that the mathematical equations formulated by DA approach are having better accuracy in comparison with regression equations.

6. Conclusions:

This research work highlights use of DA approach for developing engine performance prediction model using Buckingham π theorem for dependent variables IMEP, BP, BSFC, and IP. Following points are concluded.

1. DA approach provides the solution to establish the relationship between dependent and independent parameters and can be used for any type of fuel and at any operating conditions.
2. On residual plots, residuals are observed in the range of ± 1.1 for IMEP, ±0.5 for BP, ±0.1 for BSFC and ±0.75 for IP. Regression analysis provides accurate calculation of coefficients in mathematical equations formulated by DA.
3. Mathematical equations developed by DA are accurate. The percentage errors are 0.257, 0.547, 0.172 and 0.578 for IMEP, BP, BSFC and IP respectively. RMS errors are 5.330, 8.560, 4.199 and 8.260 for IMEP, BP, BSFC and IP respectively. This shows a good accuracy of prediction for all the mathematical relations developed by DA.
4. DA equations are more accurate compared with regression equations. This is evident from Table 5 that R Square values are ranging from 98.21 to 99.33 for DA equations in comparison with regression equations values from 76.1 to 94.9. R Square Adjusted values of DA equations are varying from 98.18 and 99.31 compared with regression equations similar values varying from 75.3 and 94.7.

DA provides the solution to establish the engine performance prediction equations with good accuracy and results. This saves the time, energy and cost for conducting actual engine test to find the performance of the engine.

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