



## Analytical Formulation for Diesel Engine Fueled with Fusel Oil/Diesel Blends

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The experiments related to reduction of gases from the exhaust emissions of internal combustion engines, usually conducted in laboratory conditions, are quite laborious and costly. For these purposes, modelling engine experiments with algorithms have emerged as a way forward. In this paper, the operation of diesel engine is modelled through experimental dataset, which has input variables such as engine load, fuel type and output variables such as carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), oxides of nitrogen (NO<sub>x</sub>), hydrocarbon (HC), smoke, Brake Specific Energy Consumption (BSEC) and maximum in-cylinder pressure (Cp<sub>max</sub>). Artificial intelligence based Symbolic Regression (SR) algorithms have been used to derive analytical equations of each output variable. The derived equations and experimental results are plotted on the same graph to show the accuracy of the obtained equations. The coefficient of determination (R<sup>2</sup>) is between 0.98 and 0.99 in all equations. In addition, Mean Error Percentage (MEP) value is less than 10 in all equations. The performance of SR algorithms is compared with Artificial Neural Network (ANN), Support Vector Machines (SVM), instance-based and K nearest based classifier (IBk), ensemble method-based bagging algorithm, and decision tree-based REPTree algorithms. SR algorithms exhibit the best performance for all output variables. IBk algorithm exhibits the second-best performance for the BSEC, CO, CO<sub>2</sub>, HC and NO<sub>x</sub> output variable. SVM algorithm exhibits the second-best performance for the Cp<sub>max</sub> output variable and Bagging algorithms exhibits the second-best performance for the smoke output variable. The operation of diesel engine can be predicted using these equations and algorithms for further research.

**Keyword:** Artificial intelligence, Diesel engine, Engine performance, Symbolic regression

### Introduction

The environment and energy equation is an important topic that has occupied humanity for a long time. Today, the balance between environment and energy represents a very important place for the healthy and sustainable life. Researchers care a lot about air pollution in the environmental pollution and say that the exhaust emissions of vehicles is the principle cause of air pollution.<sup>1,2</sup> For this reason, researchers focus on environment friendly, non-destructive, and local energy sources. Generally these energy sources are called alternative energy sources.<sup>3</sup>

Alcohol fuels are an alternative fuel type of engine fuel that can be produced from various biomass-derived plants. Alcohols contain oxygen with an increased effect on combustion efficiency and emissions.<sup>4,5</sup> Another important aspect of oxygen-rich alcohol fuels is that they can be produced by fermentation of the waste of certain plants. An important advantage is that alcohol fuels release emissions without carcinogenic effects on human

health, especially when burning oxygen-containing fuels such as ethanol and methanol. In addition, these types of fuels have the potential to be obtained from sugarcane waste, sugar beet pulp, or processed plant waste.<sup>6,7</sup>

Fusel oil is a waste alcohol variety with a biological origin. It occurs during the processing of molasses left over from sugar beet pulp. Sugar waste cake is produced during ethanol production with a lot of alcohol remainings.<sup>8</sup> There are many studies examining the effects of fusel oil as a fuel alternative in internal combustion engines with lowered emissions and increased engine performance values.<sup>9-12</sup>

Air pollution is one of the issues that humanity will face most in the future. For this reason, every effort to prevent air pollution is extremely important. The most important focus of these efforts is to reduce vehicle emissions. In recent years, researches working on motor vehicles have also focused on reducing emissions in general and using alternative fuels. But experiments with vehicles are quite laborious. For this reason, new processes predicted by computer algorithms have started to be used in recent years. Depending on various parameters, algorithms

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estimate the intermediate values of the engine or the usage values of new fuels. Artificial intelligence-based modelling of engine operation has been widely used in the literature for predicting the operation of engine when new types of fuel are used. Dey *et al.*<sup>13</sup> used the previously obtained data with the Levenberg-Marquardt algorithm to predict the effect of diesel fuel and palm oil biodiesel in compression ignition engine. Their study stated that error rates ranged from 2.32 to 4.54%. Kumar *et al.*<sup>14</sup> tried to predict an engine performance using mixtures of palm oil biodiesel, diaconal, and diesel fuel by using Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) with an error rate of 5.37% to 1.33%. Sevinç and Hanbey<sup>15</sup> studied the effects of Dibutyl Maleate (DBM) addition to diesel fuel in a coated diesel engine. By combining the data obtained from the experiments with a developed artificial intelligence technique, they made an accuracy estimate of (ANN) emission values with a margin of error of 0.25%.

In this study, artificial intelligence-based modelling of engine operation was used to help predicting the experimental results. In this modeling study, the results of the experimental study conducted by Akçay and Ozer<sup>8</sup> were used. Engine operation can be modelled as a black box, where input parameters are fuel type and engine load. Output parameters were CO, CO<sub>2</sub>, HC, BSEC, Cp<sub>max</sub> and smoke. In this study, 25 different experimental results are obtained changing the engine load and fuel type. Engine load parameters were changed from 2.5 to 12.5 Nm with a step of 2.5 Nm, i.e. 2,5 Nm, 5 Nm, 7.5 Nm, 10 Nm and 12.5 Nm. Adding fusel oil to diesel fuel was also another input parameter with a gradual change from 0% to 20% (i.e. 0%, 5%, 10%, 15% and 20%). These mixing percentage values were converted to numbers assuming 1, 0.95, 0.9, 0.85 and 0.8 for corresponding fusel oil mixing with diesel fuel, respectively. A dataset, 25 different experimental results to obtain an analytical formulation of engine operation, was used to find the complex relationship between given inputs and outputs in Fig. 1.

ANN based modeling of diesel engine have been used previously with a chosen error metric function as Mean Error Percentage (MEP). The chosen performance criteria of the model (MEP) are less than 10 in general.<sup>16</sup> In this study, the same performance criteria were chosen, and various error metric function values are noted. Symbolic macro modelling, originated from a biological phenomenon is a

modelling approach widely used to form analytical equations of various physical events.<sup>17,18</sup> The Symbolic Regression (SR) algorithm based on DataRobot Software,<sup>19</sup> was used to form analytical expressions, where inputs fuel type and engine load, and outputs are CO, CO<sub>2</sub>, HC, BSEC, Cp<sub>max</sub> and smoke. In this study, the error (MEP) of the SR algorithm model was presented comparatively with artificial neural network based ANN<sup>20</sup>, ensemble method based bagging algorithm (Bagging)<sup>21</sup>, instance-based learning algorithms and K-nearest neighbors classifiers (IBk)<sup>22,23</sup> Support Vector Machines (SVM)<sup>24</sup> and decision tree-based REPTree<sup>25</sup> algorithms.

## Material and Methods

### Experimental Setup

In this experimental study, a four-stroke and direct-injection diesel engine was used. The technical characteristics of the experimental engine used in the study are given in Table 1.

Direct current (DC) dynamometer with 10 KW of power absorption value was used in the process of experimental engine loading. Engine tests were

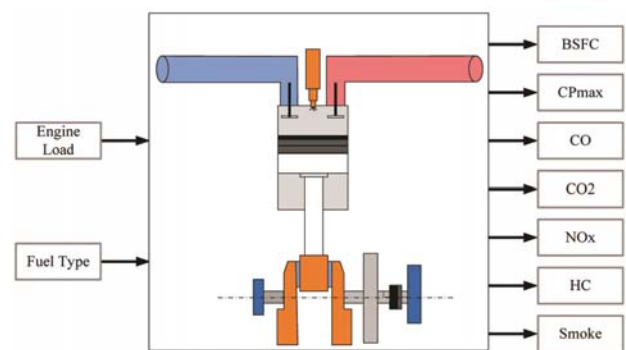


Fig. 1 — Inputs and outputs of diesel engine operation

Table 1 — Technical specification of test engine

Engine	4 stroke, direct injection, diesel engine
Number of cylinders	1
Bore x Stroke (mm)	78 × 62 mm
Compression ratio	18:1
Maximum Power (kW)	5
Valve arrangement	Overhead cam, 2 valves
Maximum engine velocity (rpm)	3000
Fuel tank capacity (litter)	3.5
Oil tank capacity (litter)	1.1
Fuel injection time (before TDC, crankshaft angle)	30
Injector opening pressure (bar)	200 ± 5

performed under constant speed of 2600 rpm and following load conditions: 2.5 Nm, 5 Nm, 7.5 Nm, 10 Nm and 12.5 Nm. In the study, commercial diesel fuel and fusel oil were mixed by 5, 10, 15 and 20% in mass. The test engine was not started until the oil temperature reached 80°C (about 5 min) before the experimental data gathering. Three consecutive tests were performed for each variable parameter and average values were presented. A schematic view of the experimental setup is given in Fig. 2.

Kistler brand 4065A2 model pressure sensor and 5011 model amplifier were used for the in-cylinder pressure measurement of the experimental engine. In the experiments, the signals from the pressure sensor were transferred to the computer with a Pico brand oscilloscope. The pressure values in the cylinder were recorded. ITALO PLUS brand exhaust gas analyzer and MRU Optrans 1600 smoke meter were used for the measurement of exhaust emissions. The technical specifications of the devices used to measure exhaust emissions are given in Table 2.

**Test Fuels**

In this study, commercial diesel fuel was mixed with fusel oil in 0%, 5%, 10%, 15% and 20% by

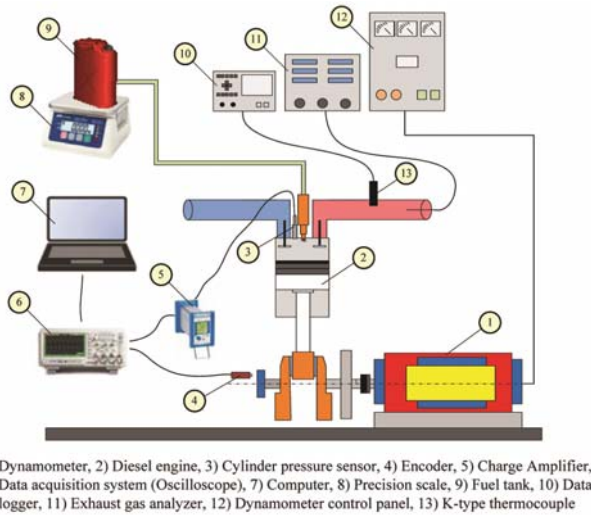


Fig. 2 — Schematic view of the experimental setup

Table 2 — Technical properties of the devices used to measure exhaust emissions

Measurement	Range	Precision
CO (% vol)	0–10	±0.06%
CO <sub>2</sub> (% vol)	0–20	±0.5%
NO <sub>x</sub> (ppm)	0–2000	±5
HC (ppm)	0–50000 n-hexan	±12
O <sub>2</sub> (% vol)	0–21	±0.1
Smoke (%)	0–100	±2%

mass, and these resulting fuels were called D, DF5, DF10, DF15 and DF20 in the study. The fusel oil used in the study was obtained from Eskişehir Sugar Plant Inc. (Eskişehir, Turkey). Table 3 shows the properties of test fuels.<sup>26</sup> When Table 3 is examined, it is seen that fusel oil contains a high amount of water. On the other hand, while the density and the viscosity values were higher than diesel fuel, the lower heating value was low.

**Symbolic Regression of Diesel Engine Operation**

DataRobot software was used for symbolic regression for the diesel engine operation. This software finds the complex relationships within the experimental data. It is based on an artificial intelligence that employs evolutionary search techniques to find mathematical equations for given inputs and outputs. In the obtained equations, trigonometric functions and constant coefficients are chosen to form analytical equations. The complexity level, number of constant coefficients, is kept the same for all equations. Input parameters are abbreviated as *f* for fuel type and *e* for engine load in the obtained equations. Various error metric functions such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), coefficient of determination (*R*<sup>2</sup>) and MEP are calculated in the Table 4.

The formula for each error metric function is given below, and an explanation of the formula is provided. MAE is the average of the absolute differences between experimental results and derived equation results. The MAE error is calculated using Eq. 1. In

Table 3 — The properties of test fuels.

Properties	Diesel	Fusel Oil
Density (kg/m <sup>3</sup> , 15°C)	828	844
Kinematic Viscosity (mm <sup>2</sup> /s, 40°C)	2.6	4.158
Flash Point (°C)	60	—
Moisture Content (%)	0.0218	13.5
Cold Filter Plugging Point (°C)	−5	—
Cetane Number	54.2	—
Lower Heating Value (MJ/kg)	43.76	29.93

Table 4 — Error metric values for proposed equations

Outputs	MAE	MSE	RMSE	R <sup>2</sup>	MEP
BSEC	0.405293	0.35762	0.598013	0.984322	2.466387
C <sub>pmax</sub>	0.692568	0.805482	0.897486	0.993799	1.410505
CO	0.013842	0.000318	0.017825	0.98858	6.537822
CO <sub>2</sub>	0.153581	0.067398	0.259612	0.981311	3.134067
HC	0.280751	0.169325	0.411491	0.995103	2.457609
NO <sub>x</sub>	11.03107	195.4575	13.98061	0.989808	2.743584
Smoke	0.684633	1.116006	1.056412	0.998524	8.173762

all equation,  $y_i$  and  $\hat{y}_i$  correspond to the experimental results and obtained equation results, respectively. Whereas  $n$  is the total number of samples in all equations. MSE is the average of the squared differences between experimental results and derived equation results. The MSE error is calculated using Eq. 2. RMSE is the square root of the mean squared error, which is the average squared difference between experimental results and derived equation results. The RMSE error is calculated using Eq. 3.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad \dots (1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad \dots (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad \dots (3)$$

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad \dots (4)$$

$$SST = \sum_{i=1}^n (y_i - \bar{y})^2 \quad \dots (5)$$

$$R^2 = \frac{SST - SSE}{SST} \quad \dots (6)$$

$$MEP = 100 \times \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) / (y_i) \quad \dots (7)$$

$R^2$  is the Sum of Square Errors (SSE) and the Sum of Square Total (SST). SSE is the sum of the squared differences between the experimental results and the derived equation results as it can be found in Eq. 4. In addition, SST is the sum of the squared differences between the experimental results and derived equation results as it can be found in Eq. 5. Therefore, The  $R^2$  error can be defined by using Eq. 4 and Eq. 5 in Eq. 6. MEP is the average of the absolute differences between the experimental results and derived equation results. The MEP error is calculated using Eq. 7. The MAE, MSE, RMSE,  $R^2$  and MEP errors of each equation are given in Table 4.

$R^2$  error is between 0.98 and 0.99 in all equations in Table 4. MEP error value is less than 10 in all equations in Table 4, which is acceptable in the literature. MAE, MSE and RMSE error values are also given in Table 4 to show the accuracy of the obtained equations comparing to experimental results. The coefficients of all equations are given in Table 5. There are six coefficients in all equations named as  $a_0, a_1, a_2, a_3, a_4, a_5$  and  $a_6$ . The values of these coefficients are given from  $a_0$  to  $a_3$  in first part of the table, and from  $a_4$  to  $a_6$  in the second part of the Table 5.

**Exhaust Emissions**

In this section, comparison of experimental and derived equation results of CO, CO<sub>2</sub>, NO<sub>x</sub>, smoke and HC emissions was given. CO emissions are known as a product of partial combustion caused by insufficient oxygen during combustion.<sup>27</sup> The air/fuel ratio, fuel type, fuel atomization rate, combustion chamber shape, engine load and speed, injector pressure and combustion duration are important parameters affecting the formation of CO emission.<sup>16</sup>

Table 5 — The coefficients of derived equations

Outputs	$a_0$	$a_1$	$a_2$
BSEC	43.470415382833	0.0269929283011139	1.72497792920531
Cp <sub>max</sub>	223.76218975246	3.52813610392691	0.0419993460976
CO	0.151160072973675	0.213163330682813	0.00577244261142511
CO <sub>2</sub>	1.51558273826975	1.13972446784046	1.82713628362646
HC	19.9372994000517	0.314726447451887	0.000146846839662765
NO <sub>x</sub>	126.870924353878	219.73664023219	18.1106658678194
Smoke	1.63662926320045	0.290915831655702	0.000335018523441724
Outputs	$a_3$	$a_4$	$a_5$
BSEC	3.87780858050448	7.72676405070718	0.0131578603937159
Cp <sub>max</sub>	320.878142759528	4.66451853514415	183.076129345547
CO	0.00605770019260288	0.000190195581321146	0.0604564845475391
CO <sub>2</sub>	0.720690923587298	0.119662350182658	1.6323791280479
HC	14.142135623731	0.0309165857153068	0.1243768045366
NO <sub>x</sub>	170.179230865013	0.388828745774277	14.142135623731
Smoke	0.554964802815258	0.00138199707970426	0.499468322533732

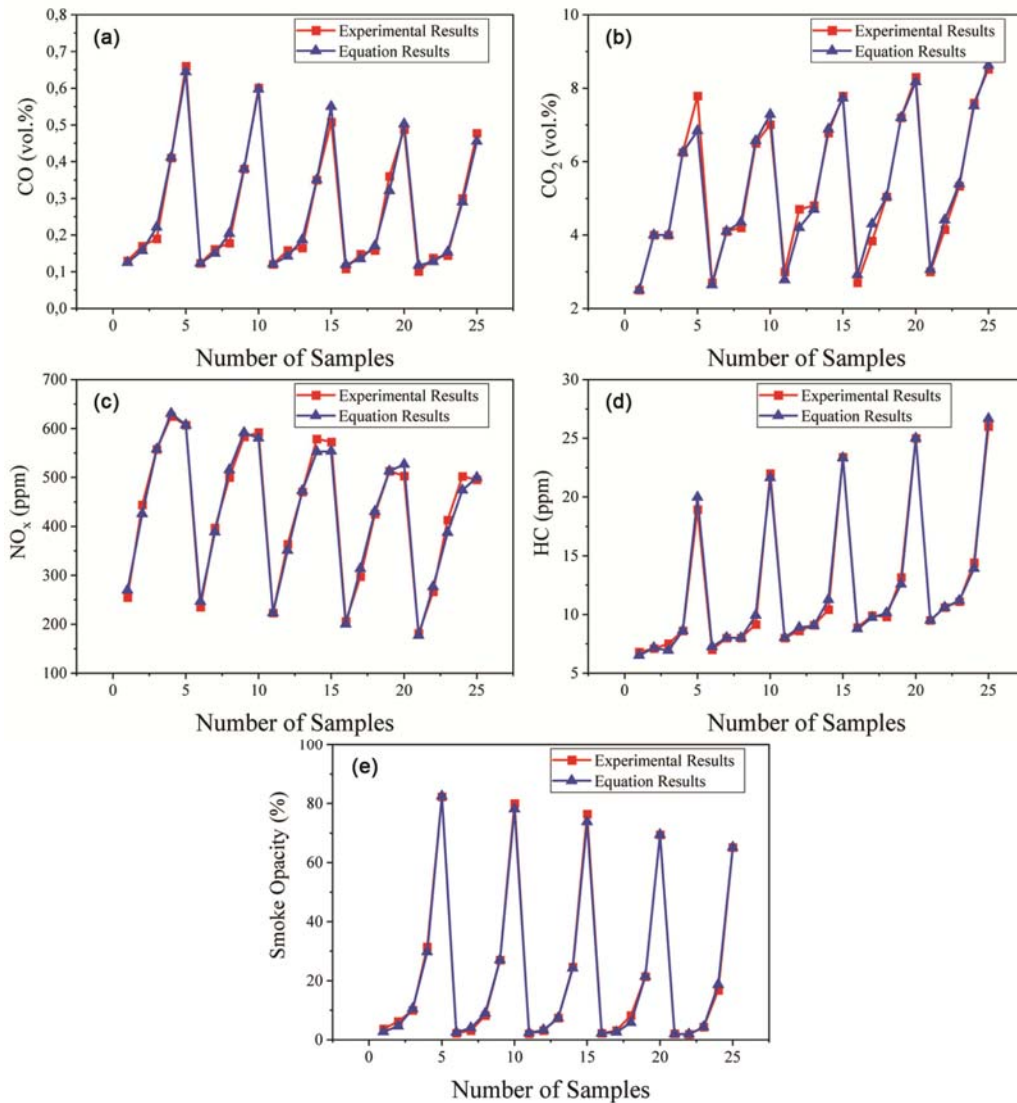
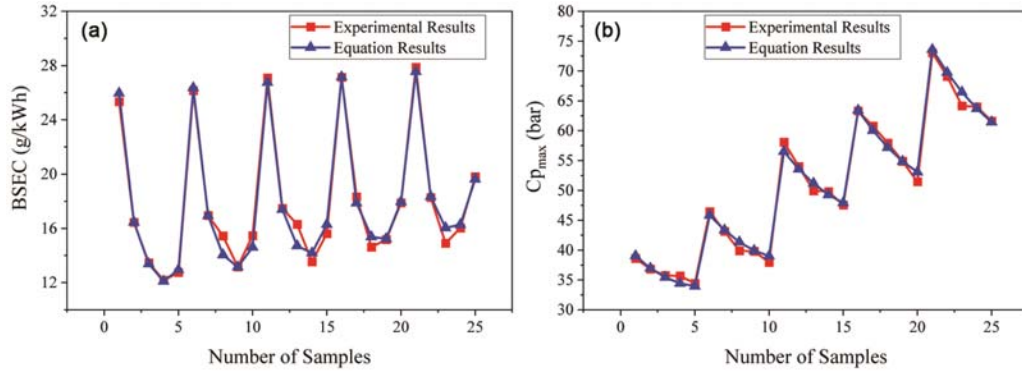


Fig. 3 — Comparison of experimental and derived equation results of exhaust emissions, a) CO, b) CO<sub>2</sub>, c) NO<sub>x</sub>, d) HC, e) Smoke

The calculation of CO is given in Eq. 8, and it is plotted with experimental results to show the accuracy of the derived equation in Fig. 3(a). Carbon dioxide (CO<sub>2</sub>), a type of greenhouse gas, is produced as a result of the complete combustion of carbon and oxygen in fossil-derived fuel.<sup>28</sup> The calculation of CO<sub>2</sub> is given in Eq. 9, and it is plotted with experimental results to show the accuracy of the derived equation in Fig. 3(b). NO<sub>x</sub> emissions consist of three main factors: combustion temperature, oxygen concentration and nitrogen exposure time to high temperature.<sup>29</sup> NO<sub>x</sub> absorption pollutes the atmosphere and causes acid rain.<sup>30</sup> The calculation of NO<sub>x</sub> is given in Eq. 10, and it is plotted with

experimental results to show the accuracy of the derived equation in Fig. 3(c). Smoke emissions are mainly caused by incomplete combustion of fuel in fuel-rich areas within the combustion chamber. The high viscosity and poor volatility of the fuel lead to uneven distribution of fuel droplets, forming local fuel-rich regions.<sup>31</sup> The calculation of smoke is given in Eq. 11, and it is plotted with experimental results to show the accuracy of the derived equation in Fig. 3(d). Hydrocarbon (HC) emissions are caused by incomplete combustion of fuel during the combustion process.<sup>31</sup> The calculation of HC is given in Eq. 12, and it is plotted with experimental results to show the accuracy of the derived equation in Fig. 3(e).


 Fig. 4 — Comparison of Experimental and Derived Equation Results of (a) BSEC, (b)  $Cp_{max}$ 

The error metric values of the Eqs 8–12 are given in Table 4. In addition, the coefficients of Eqs 8–12 are listed in Table 5.

$$CO = -a_0 + e \times (a_1 + a_2 \times e^2 + a_3 \times f \times e - a_4 \times e^3 - a_5 * e) \quad \dots (8)$$

$$CO_2 = a_0 + e \times (a_1 - a_3 \times f) + \sin(e) \times (a_2 - a_4 \times e - a_5 \times f) \quad \dots (9)$$

$$NO_x = a_0 + e \times (a_2 \times e - a_3 - a_4 \times e^2) + e \times f \times (a_1 - a_5 \times e) \quad \dots (10)$$

$$Smoke = a_0 + e \times (a_1 + a_2 \times e^4 + a_3 \times f \times e - a_4 \times e^3 - a_5 \times e) \quad \dots (11)$$

$$HC = a_0 + e^2 \times (a_1 + e \times \sin(a_2 \times e^2) - a_4 \times e) - f \times (a_3 + a_5 \times e^2) \quad \dots (12)$$

### Engine Performance

In this section, the comparison of experimental and derived equation results of Brake Specific Energy Consumption (BSEC) and maximum cylinder pressure ( $Cp_{max}$ ) was given. BSEC is defined as the total amount of fuel energy required to produce 1 KW of useful work per hour.<sup>32</sup> Fuel consumption of diesel engine depends on the correlation between viscosity, fuel density, lower heating value of fuel and volumetric fuel injection system.<sup>33</sup> The calculation of BSEC is given in Eq. 13, and it is plotted with experimental results to show the accuracy of the derived equation in Fig. 4(a). The error metric values of the Eq. 13 are given in Table 4. The coefficients of Eq. 13 are listed in Table 5.

$$BSEC = a_0 + e \times (a_1 \times e^2 - a_3) + a_2 \times \cos(0.7 \times e) - f \times (a_4 + a_5 \times e^3) \quad \dots (13)$$

In internal combustion engines,  $Cp$  is the most important parameter used in the analysis of the combustion process.<sup>34</sup> The calculation of  $Cp_{max}$  is given in Eq. 14, and it is plotted with experimental results to

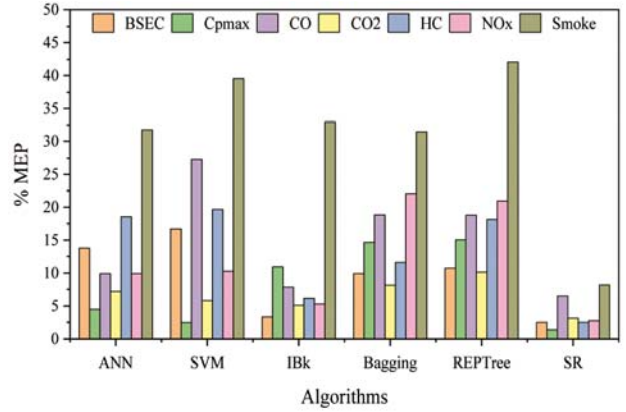


Fig. 5 — Error Metric Comparison of All Algorithms

Table 6 — MEP Value comparison of all algorithms

Algorithms/ Outputs	ANN	SVM	IBk	Bagging	REPTree	SR
BSEC	13.77	16.74	3.33	9.91	10.77	2.47
$Cp_{max}$	4.49	2.45	10.97	14.65	15.05	1.41
CO	9.93	27.31	7.83	18.83	18.77	6.54
CO <sub>2</sub>	7.15	5.84	5.13	8.13	10.16	3.13
HC	18.52	19.64	6.19	11.65	18.10	2.46
NO <sub>x</sub>	9.92	10.29	5.33	22.07	20.95	2.74
Smoke	31.77	39.52	32.97	31.44	42.08	8.17

show the accuracy of the derived equation in Fig. 4(b). The error metric values of the Eq. 14 are given in Table 4. The coefficients of Eq. 14 are listed in Table 5.

$$Cp_{max} = a_0 + \cos(a_3 \times f) + f \times (a_1 \times e - a_5) + e \times (a_2 \times e - a_4) \quad \dots (14)$$

Where  $f$  is the fuel type and  $e$  is the engine load.

### Error Metric Comparison of Algorithms

In this section, top classification algorithms such as ANN, Bagging, IBk, REPTree and SVM were used for regression of output variables. Their error metric

values such as MEP were compared with SR (Fig. 5 and Table 6). As it can be seen in Fig. 5, SR algorithm exhibited the best performance with all output variables. IBk algorithm exhibited the second-best performance for the BSEC, CO, CO<sub>2</sub>, HC, NO<sub>x</sub> output variables. SVM algorithm yielded the second-best performance for the Cp<sub>max</sub> output variable. Bagging algorithms exhibited the second-best performance for the smoke output variable.

### Conclusions

In this study, modeling of the diesel engine is realized with experimental dataset. The proposed model has engine load, fuel type as input variables, and CO, CO<sub>2</sub>, NO<sub>x</sub>, HC, BSEC, Cp<sub>max</sub>, and smoke as output variables. Artificial intelligence-based SR algorithm is used to find analytical equations between given inputs and output variables. The result of SR algorithm is compared with experimental results by plotting on the same graph. Furthermore, error metric functions such as MAE, MSE, RMSE, R<sup>2</sup>, and MEP are calculated to show the accuracy of the obtained equations. It has been seen that the MEP value is less than 10 in all equations. The best equation has 1.41 MEP error value for Cp<sub>max</sub> variable. The worst equation has 8.1 MEP error value for smoke variable. R<sup>2</sup> error metric value is 0.98 or 0.99 in all equations. In addition, performance of the SR algorithm is compared with top classification algorithms such as ANN, SVM, IBk, Bagging and REPTree algorithms. SR algorithm exhibits the best performance for all output variables. IBk algorithm exhibits the second-best performance for BSEC, CO, CO<sub>2</sub>, HC, NO<sub>x</sub> output variables, whereas SVM algorithm exhibits the second-best performance for only Cp<sub>max</sub> output variable. Lastly, Bagging algorithm exhibits the second-best algorithm for only smoke output variable. In conclusion, diesel engine operation can be predicted by using either the obtained equations or given algorithms with the acceptable error value for further research.

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### Conflict of Interest

The authors declared no conflict of interest.

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