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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_2), oxides of nitrogen (NO_x), hydrocarbon (HC), smoke, Brake Specific Energy Consumption (BSEC) and maximum in-cylinder pressure (Cp_{max}). 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^2) 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_2, HC and NO_x output variable. SVM algorithm exhibits the second-best performance for the Cp_{max} 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.[1,2] For this reason, researchers focus on environment friendly, non-destructive, and local energy sources. Generally these energy sources are called alternative energy sources.[3]

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.[4,5] 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.[6,7]

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.[8] 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.[9–12]

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.*[13] 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.*[14] 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[15] 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 Akcay and Ozer[8] 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_2, HC, BSEC, Cp_{max} 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.[16] 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.[17,18] The Symbolic Regression (SR) algorithm based on DataRobot Software,[19] was used to form analytical expressions, where inputs fuel type and engine load, and outputs are CO, CO_2, HC, BSEC, Cp_{max} and smoke. In this study, the error (MEP) of the SR algorithm model was presented comparatively with artificial neural network based ANN[20], ensemble method based bagging algorithm (Bagging)[21], instance-based learning algorithms and K-nearest neighbors classifiers (IBk)[22,23] Support Vector Machines (SVM)[24] and decision tree-based REPTree[25] 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

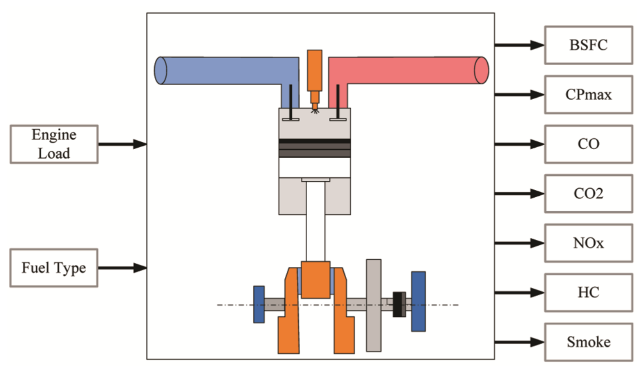


Fig. 1 — Inputs and outputs of diesel engine operation

Table 1 — Technical specification of test engine

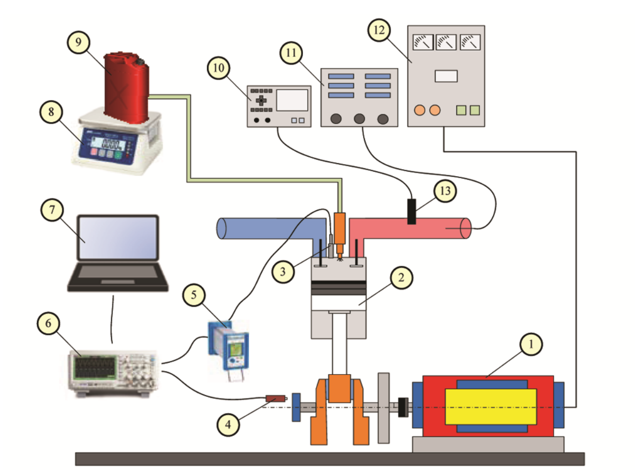
Engine	4 stroke, direct injection, diesel engine
Number of cylinders	1
Bore x Stroke (mm)	78 × 62 mm
Compression ratio	18:1
Maximum Power (kW)	5
Valve arrangement	Overhead cam, 2 valves
Maximum engine velocity (rpm)	3000
Fuel tank capacity (litter)	3.5
Oil tank capacity (litter)	1.1
Fuel injection time (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 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.[26] 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.



1) Dynamometer, 2) Diesel engine, 3) Cylinder pressure sensor, 4) Encoder, 5) Charge Amplifier, 6) Data acquisition system (Oscilloscope), 7) Computer, 8) Precision scale, 9) Fuel tank, 10) Data logger, 11) Exhaust gas analyzer, 12) Dynamometer control panel, 13) K-type thermocouple

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_2 (% vol)	0–20	±0.5%
NO_x (ppm)	0–2000	±5
HC (ppm)	0–50000 n-hexan	±12
O_2 (% vol)	0–21	±0.1
Smoke (%)	0–100	±2%

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^2) 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^3, 15°C)	828	844
Kinematic Viscosity (mm^2/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^2	MEP
BSEC	0.405293	0.35762	0.598013	0.984322	2.466387
Cp_{max}	0.692568	0.805482	0.897486	0.993799	1.410505
CO	0.013842	0.000318	0.017825	0.98858	6.537822
CO_2	0.153581	0.067398	0.259612	0.981311	3.134067
HC	0.280751	0.169325	0.411491	0.995103	2.457609
NO_x	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.

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

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

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

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

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

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

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

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_2, NO_x, smoke and HC emissions was given. CO emissions are known as a product of partial combustion caused by insufficient oxygen during combustion.[27] 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.[16]

Table 5 — The coefficients of derived equations

Outputs	a_0	a_1	a_2
BSEC	43.470415382833	0.0269929283011139	1.72497792920531
Cp_{max}	223.76218975246	3.52813610392691	0.0419993460976
CO	0.151160072973675	0.213163330682813	0.00577244261142511
CO_2	1.51558273826975	1.13972446784046	1.82713628362646
HC	19.9372994000517	0.314726447451887	0.000146846839662765
NO_x	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_{max}	320.878142759528	4.66451853514415	183.076129345547
CO	0.00605770019260288	0.000190195581321146	0.0604564845475391
CO_2	0.720690923587298	0.119662350182658	1.6323791280479
HC	14.142135623731	0.0309165857153068	0.1243768045366
NO_x	170.179230865013	0.388828745774277	14.142135623731
Smoke	0.554964802815258	0.00138199707970426	0.499468322533732

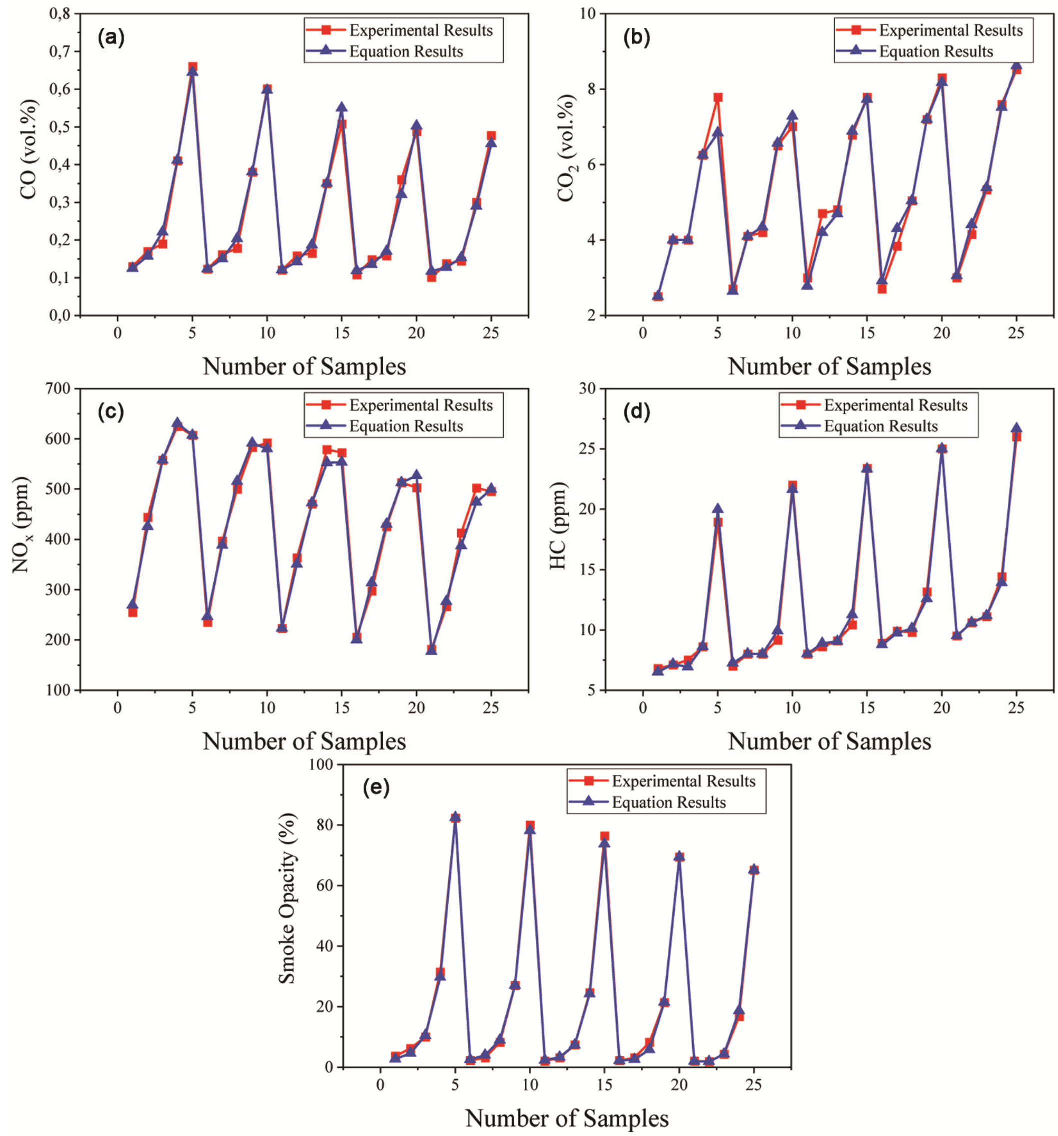


Fig. 3 — Comparison of experimental and derived equation results of exhaust emissions, a) CO, b) CO_2, c) NO_x, d) HC, e) Smoke

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_2), a type of greenhouse gas, is produced as a result of the complete combustion of carbon and oxygen in fossil-derived fuel.[28] The calculation of CO_2 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_x emissions consist of three main factors: combustion temperature, oxygen concentration and nitrogen exposure time to high temperature.[29] NO_x absorption pollutes the atmosphere and causes acid rain.[30] The calculation of NO_x 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.[31] 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.[31] 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).

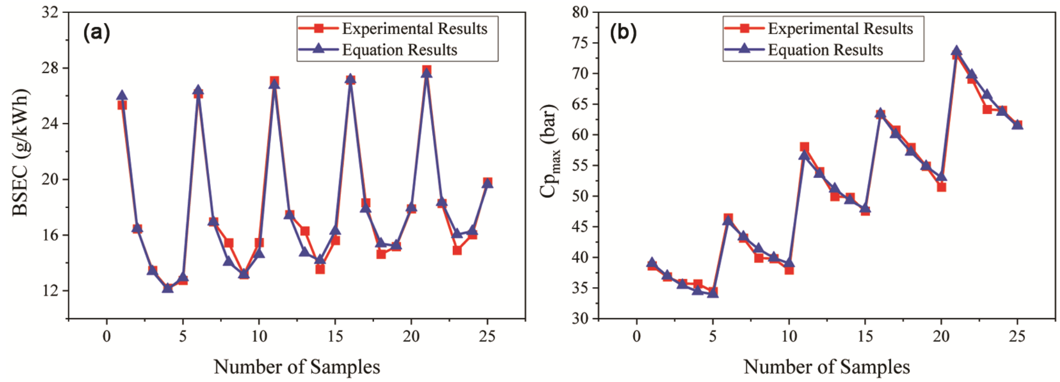


Fig. 4 — Comparison of Experimental and Derived Equation Results of (a) BSEC, (b) Cp_{max}

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.

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

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

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

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

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

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.[32] Fuel consumption of diesel engine depends on the correlation between viscosity, fuel density, lower heating value of fuel and volumetric fuel injection system.[33] 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.

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

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

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

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

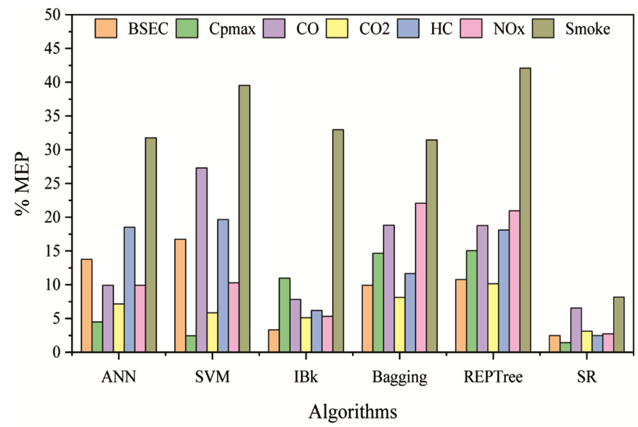


Fig. 5 — Error Metric Comparison of All Algorithms

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_2	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_x	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

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_2, HC, NO_x output variables. SVM algorithm yielded the second-best performance for the Cp_{max} 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_2, NO_x, HC, BSEC, Cp_{max}, 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^2, and MEP are calculated to show the accuracy of the obtained equations. It has seen that the MEP value is less than 10 in all equations. The best equation has 1.41 MEP error value for Cp_{max} variable. The worst equation has 8.1 MEP error value for smoke variable. R^2 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 exhibit the second-best performance for BSEC, CO, CO_2, HC, NO_x output variables, whereas SVM algorithm exhibit the second-best performance for only Cp_{max} 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.

References

1 Liu W, Shadloo M S, Tlili I, Maleki A & Bach Q V, The effect of alcohol–gasoline fuel blends on the engines' performances and emissions, *Fuel*, **276** (2020) 117977.

2 Lee Z, Kim T, Park S & Park S, Review on spray, combustion, and emission characteristics of recent developed direct-injection spark ignition (DISI) engine system with multi-hole type injector, *Fuel*, 259 (2020) 116209.

3 Stančina H, Mikulčićab H, Wang X & Duić N, A review on alternative fuels in future energy system, *Renew Sustain Energy Rev*, **128** (2020) 109927.

4 Ardebili SMS, Solmaz H, İpci D, Calam A & Mostafaei M, A review on higher alcohol of fusel oil as a renewable fuel for internal combustion engines: Applications, challenges, and global potential, *Fuel*, **279** (2020) 118516.

5 Uyumaz A, An experimental investigation into combustion and performance characteristics of an HCCI gasoline engine fueled with n-heptane, isopropanol and n-butanol fuel blends at different inlet air temperatures, *Energy Convers Manag*, **98** (2015) 199–207.

6 Rahman Q M, Zhang B, Wang L & Shahbazi A, A combined pretreatment, fermentation and ethanol-assisted liquefaction process for production of biofuel from Chlorella sp., *Fuel*, **257** (2019) 116026.

7 Yesilyurt M K, A detailed investigation on the performance, combustion, and exhaust emission characteristics of a diesel engine running on the blend of diesel fuel, biodiesel and 1-heptanol (C7 alcohol) as a next-generation higher alcohol, *Fuel*, **275** (2020) 117893.

8 Akcay M & Ozer S, Experimental investigation on performance and emission characteristics of a CI diesel engine fueled with fusel oil/diesel fuel blends, *Energy Sources A: Recovery Util Environ Eff*, (2019) 1–16. https://doi.org/10.1080/15567036.2019.1689317.

9 Awad O I, Ali O M, Hammid A T & Mamat R, Impact of fusel oil moisture reduction on the fuel properties and combustion characteristics of SI engine fueled with gasoline-fusel oil blends, *Renewable Energy*, **123** (2018) 79–91.

10 Ardebili SMS, Solmaz H & Mostafaei M, Optimization of fusel oil–gasoline blend ratio to enhance the performance and reduce emissions, *Appl Therm Eng*, **148** (2019) 1334–1345.

11 Yılmaz E, Investigation of the effects of diesel-fusel oil fuel blends on combustion, engine performance and exhaust emissions in a single cylinder compression ignition engine, *Fuel*, **255** (2019) 115741.

12 Alenezi, R A, Erdiwansyah, Mamat R, Norkhizan A M & Najafi G, The effect of fusel-biodiesel blends on the emissions and performance of a single cylinder diesel engine, *Fuel*, **279** (2020) 118438.

13 Dey S, Reang N M, Majumder A, Deb M & Das P K, A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend, *Energy*, **202** (2020) 117813.

14 Kumar A N, Kishore P S, Raju K B, Ashok B, Vignesh R, Jeevanantham A K, Nanthagopal K & Tamilvanan A, Decanol proportional effect prediction model as additive in palm biodiesel using ANN and RSM technique for diesel engine, *Energy*, **213** (2020) 119072.

15 Sevinç H & Hazar H, Investigation of performance and exhaust emissions of a chromium oxide coated diesel engine fueled with dibutyl maleate mixtures by experimental and ANN technique, *Fuel,* **218** (2020) 118338.

16 Ağbulut Ü, Ayyıldız M & Sarıdemir S, Prediction of performance, combustion and emission characteristics for a dual fuel diesel engine at varying injection pressures, *Energy*, **197** (2020) 117257.

17 Stoutemyer D R, Can the Eureqa symbolic regression program, computer algebra and numerical analysis help each other? *Notices AMS*, **60(6)** (2013) 713–724.

18 Satılmış G, Güneş F & Mahouti P, Physical parameter-based data-driven modeling of small signal parameters of a metal-semiconductor field-effect transistor, *Int J Numer Model El*, *(*2020) e2840.

19 Schmidt M & Lipson H, Distilling Free-Form Natural Laws from Experimental Data, *Science*, **324** (2009) 81–85.

20 Hazar H, Tekdogan R & Sevinc H, Investigating the effects of oxygen enrichment with modified zeolites on the performance and emissions of a diesel engine through experimental and ANN approach, *Fuel*, **303** (2021) 121318.

21 Breiman L, Bagging predictors, *Machine Learning*, **24** (1996) 123–140.

22 Aha D W & Kibler D, Instance-based learning algorithms, *Machine Learning*, **6** (1991) 37–66.

23 Satılmış G, Güneş F & Mahouti P, Physical parameter-based data driven modeling of small signal parameters of a metal-semiconductor field-effect transistor, *Int J Numer Model*, **34** (2021) e2840.

24 Shevade S K, Keerthi S S, Bhattacharyya C & Murthy K K, Improvements to the SMO Algorithm for SVM Regression, *IEEE Trans Neural Network*, **11** (2000) 1188–1193.

25 Rajesh P & Karthikeyan M, A comparative study of data mining algorithms for decision tree approaches using WEKA tool, *Adv Nat Appl Sci*, **11** (2017) 230.

26 Awad OI, Mamat R, Ali OM, Azmi WH, Kadirgama K, Yusri IM. Response surface methodology (RSM) based multi-objective optimization of fusel oil -gasoline blends at different water content in SI engine. *Energy Convers Manag,* **150** (2017) 222–241.

27 Ruhul A M, Kalam M A, Masjuki H H, Shahir S A, Alabdulkarem A, Teoh Y H, How H G & Reham S S, Evaluating combustion, performance and emission characteristics of Millettia pinnata and Croton megalocarpus biodiesel blends in a diesel engine, *Energy*, **141** (2017) 2362–2376.

28 Wu H W & Wu Z Y, Investigation on combustion characteristics and emissions of diesel/hydrogen mixtures by using energy-share method in a diesel engine, *Appl Therm Eng*, **42** (2012) 154–162.

29 Hosseini S M, Ahmadi R, Performance and emissions characteristics in the combustion of co-fuel diesel-hydrogen in a heavy duty engine, *Applied Energy*, **205** (2017) 911–925.

30 Dinesha P, Kumar S & Rosen M A, Combustion, performance, and emissions of a compression ignition engine using Pongamia biodiesel and bioethanol, *Environ Sci Pollut Res*, **26** (2019) 8069–8079.

31 Hajlari SA, Najafi B & Ardabili S F, Castor oil, a source for biodiesel production and its impact on the diesel engine performance, *Renew Energy Focus*, **28** (2019) 1–10.

32 Alrazen, HA, Talib A R A, Adnan R & Ahmad K A, A review of the effect of hydrogen addition on the performance and emissions of the compression–Ignition engine, *Renew Sustain Energy Rev*, **54** (2016) 785–796.

33 Raman L A, Deepanraj B, Rajakumar S & Sivasubramanian V, Experimental investigation on performance, combustion and emission analysis of a direct injection diesel engine fuelled with rapeseed oil biodiesel, *Fuel*, **246** (2019) 69–74.

34 Kumar R & Gakkhar R P, Influence of nozzle opening pressure on combustion, performance and emission analysis of waste cooking oil biodiesel fuelled diesel engine, *Int J Renew Energy Technol*, **9** (2018) 244–59.