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Prediction of Low Heat Rejection engine performance parameters using Regression: A machine learning approach

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ABSTRACT

The Low Heat Rejection engine (LHR) is useful to reduce the engine coolant heat losses thereby improving the combustion engine performance. The key performance measurements namely Brake Thermal Efficiency (BTE), Brake Mean Effective Pressure (BMEP) and Brake Power (BP) are calculated for analyzing the performance and efficiency of the engine when the blend of algae oil, diethyl ether and copper nanoparticles is injected into medium grade LHR engine. However, factors such as injection pressure, injection timing, exhaust gas temperature, coolant load and volumetric efficiency have their effect on the estimations of these performance parameters. To estimate the LHR engine performance for better engine efficiency, machine learning based Multiple Regression modeling is implemented. The physical medium grade LHR engine experimental setup is done and the experiments are carried out. The operational parameters (factors) and key performance parameters data are gathered from these experiments, exploratory data analysis is then carried out, relevant operational parameters that influence the performance parameters are identified which are then used for learning the regression- based models that estimate the performance of the medium grade LHR engine. These models are validated to ensure have better generalization capabilities to unseen data. It is observed that a high R-squared value of 1 for BTE and BP performance parameters and very less Mean Square Error value of 5.259072701473412e-31 for BMEP performance parameter are achieved. These values prove that machine learning help optimize LHR engine operation and reduce downtime.

***Key words**: LHR Engine, Algae oil blend, BTE, BMEP, BP, Regression, R-squared, MSE.*

Introduction

The internal combustion (IC) engines which are part of transportation technology are typically powered by hydrocarbon-based fuels like natural gas, gasoline, diesel fuel (Wallner, and Miers (2012). These fuels emit pollutants like Cox (Resitoglu *et al.*, 2015) and other compounds. Also, these fuels exhibit incomplete combustion, are of poor quality thereby increasing the chances of its downtime. To avoid

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this, the IC engines are insulated in the path of heat flow to the coolant. These type of IC engines are termed as Low Heat Rejection (LHR) engines. However, there is an imminent need to replace the hydrocarbon-based fuels with low carbon alternate renewable fuels such as the combination of algae oil with diethyl ether and copper nanoparticles. This algae oil blend when used with LHR engines will potentially reduce the engine downtime and emit less percentage of pollutants.

The performance of the algae oil blend based LHR engine is assessed with the help of key performance measurements namely Brake Thermal Efficiency, Brake Mean Effective Pressure and Brake Power. However, factors such as injection pressure, injection timing, exhaust gas temperature, coolant load and volumetric efficiency have their effect on the estimations of these performance parameters.

To estimate the medium grade LHR engine performance with the injection of algae oil blend into it, the Multiple Regression based data-driven modeling is implemented. The LHR engine operational parameters and performance parameters data are gathered, exploratory data analysis (EDA) is carried out, relevant operational parameters that influence the performance parameters are identified from EDA, which are then used for learning the regression-based models that estimate the performance of the medium grade LHR engine. These machine learning models are validated to ensure have better generalization capabilities to unseen data. The performance predictions obtained from regression models help optimize the LHR engine operation and reduce downtime.

Related Works

Performance, combustion, and emission characteristic studies of the LHR engine involve lots of parameters. Several tests are to be performed to find the relation between various parameters. High-precision instruments and equipment are required to measure the different operating parameters with both biofuels and blend fuels. These tests are expensive and time-consuming (Shrivastava and Khan, 2017; Kannan *et al*., 2013).

The research on integration of machine learning techniques with LHR engine has proved to be very useful in the recent past. LHR engines have the potential to improve fuel efficiency which in turn improves the performance of the engine. Also, learning the predictive models reduce the time and experimentation cost.

Bhatt, A.N. and Shrivastava, N. (2022) performed extensive review on the application of Artificial Neural Network (ANN) for IC engines to understand the engine predictive capabilities. Rezaei *et al.* (2015) analyzed Homogeneous charge compression ignition (HCCI) engine performance. HCCI engine is a specific type of LHR engine. They developed ANN models to predict various engine performance parameters like BTE, in-cylinder pressure etc., with butanol and ethanol blend. The authors developed feed-forward and radial basis functionbased ANN models and achieved 4% Mean Absolute Percentage Error (MAPE) indicating predictions are closer to the actual engine performance values.

Agarwal, T. *et al*. (2020) implemented multiple regression supervised learning technique to predict the compression ignition engine performance parameters and observed high error percentage of 6.37% for BTE parameter and insignificant error percentage for Brake Specific Fuel Consumption (BSFC) parameter. Sanjeevannavar, M.B. *et al.* (2023) utilized various machine learning methods namely XGBoost, Random Forest Regressor, Decision Tree Regressor and Linear Regression. It is observed that XGBoost has achieved 0.248 Mean Square Error (MSE), Random Forest Regressor has achieved 0.441 MSE, Decision Tree Regressor has achieved 0.727 MSE and Linear Regression has achieved 4.587 MSE.

The above works on regression modeling has motivated the authors of this manuscript to implement multiple regression to predict the LHR engine performance parameters namely BTE, BMEP and BP with the aim to achieve very less error percentages.

Materials and Methods

The algae oil blended with diethyl ether (DEE) was injected through normal conventional system. The algae oil was also blended with copper nano particles. The exhaust emissions of Particulate matter (PM), Oxides of nitrogen (NO_x), carbon monoxide (CO) emissions and un-burnt hydro carbons (UBHC) were determined with algae oil blended with varied injection pressure and data was compared with neat diesel fuel operation on conventional engine. The nano particles are added 20 mg of the one litre solution of test fuel. The preparation of the copper nano particles was mentioned in (Mohammed *et al.*, 2021).

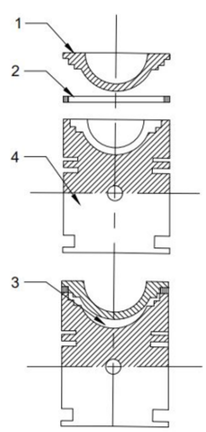
Table 1. Properties of algae fuel

	Algae Oil	Diesel
Specific Gravity at 40°C	0.91	0.84
Cetane Number	51	55
Viscosity at 40°C	4.84 mm^2/s	3.0mm^2/s
Calorific Value	41MJ/kg	42MJ/kg

Fabrication of Combustion Chamber of Medium grade LHR engine

Fig. 1 shows assembly details of combustion chamber of medium degree insulated engine.

It contained a two-part piston; the top crown (1) made of low thermal conductivity material, stainless steel (A-304 Grade-B) screwed to aluminum body of the piston by keeping a gasket made of stainless steel (2), providing an optimum air gap (3) 2.8 mm in between the crown and the body (4) of the piston. The optimum thickness of air gap in the air gap piston was found to be 2.8 mm for improved performance of the engine with stainless steel insert and diesel as fuel A stainless steel insert (5) was screwed to the top portion of the liner in such a manner that an optimum air gap (7) of 2.8 mm was maintained between the insert and the liner body (6). At 500°C the thermal conductivity of stainless steel (A 304 Grade-B) and air are 16.0 and 0.057 W/m-K respectively. Stainless steel employed by the authors is plenty available, good machinability characteristics and less expensive.



1. Stainless steel crown, 2. Stainless steel gasket, 3. Air gap in the piston, 4 Body of the piston.

Fig. 1. Combustion chamber of the medium grade insulated diesel engine

Experimental set up

Fig. 2 shows that the test engine (1) and the details of the algae fuel are given in Table 1. Table 2 shows the specification of the experimental engine. It was located at Applied Thermo Dynamics Laboratory of MED, CBIT, Hyderabad. The engine was connected to power measuring device (2). The engine had computerized test bed. There was facility of loading the engine by means of variable rheostat (3). The mass flow rate of air was measured by an orifice meter (4), U-tube water manometer (5) and air box (6). Air box will reduce pressure oscillations in intake manifold. Fuel circuit consisted of components, fuel tank (7), three way valve (8) and burette (9).

Table 2. Details of the engine

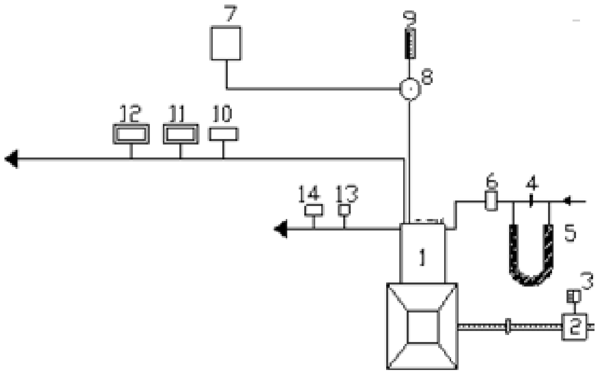
Description	Specification
Make	Kirloskar
Number of cylinders	01
Number of Strokes	04
Ratio of bore to stroke	80 mm/110 mm
Power	3.68 kW (5 HP) at the rated speed of 1500 rpm
Compression Ratio	16.5:1
Type of cooling Arrangement	Water cooling
Recommended Injection Pressure	190 bar
Recommended Injection Timing	27 degrees before top dead centre

The temperature of the exhaust gas was indicated with exhaust gas temperature sensor (10). The particulate levels were determined with AVL Smoke meter (11) at full load operation. The pollutants of CO and UBHC were determined by Netel Chromatograph multi gas analyzer (12) at full load operation. The range and accuracy of the analyzers in multi gas analyzer are shown in Table 3. Outlet jacket water temperature was indicated with temperature sensor (13). The flow of the coolant was measured with flow meter (14). The engine was provided with gravity lubrication system. Algae oil blended with optimum quantity of 15% by DEE, which in turn mixed with nano particles of copper. There was facility to increase injection pressure by means of nozzle testing device. .

The test fuels of the investigations were i) neat diesel and ii) Algae oil blended with 15% diethyl ether and copper nano particles. The performance characteristics were determined at full load of the engine, at recommended injection timing (RIT) and

Table 3. Range and accuracy of Analyzers

S.No	Name of the Analyzer	Principle adopted	Range	Accuracy
1	AVL Smoke Analyzer	Opacity	0-100 HSU±1 HSU (Hartridge Smoke Unit)	
2	Netel ChromatographCO analyzer	Infrared absorption spectrograph	0-10%	± 0.1%
3	Netel ChromatographUBHC analyzer	NDIR	0-1000 ppm	±5 ppm
4	Netel ChromatographNO_x analyzer	Chemiluminiscence	0-5000pm	±5 ppm



1. Engine, 2. Electical Dynamometer, 3. Load Box, 4. Orifice flow meter, 5. U-tube water manometer, 6. Air box, 7.Fuel tank, 8, Pre-heater, 9. Burette, 10. Exhaust gas temperature indicator, 11.AVL Smoke meter, 12. Netel Chromatograph NOx Analyzer, 13. Outlet jacket water temperature indicator, 14. Outlet-jacket water flow meter.

Fig. 2. Schematic diagram of experimental set-up

optimum injection timing (OIT) with algae fuel blended with an optimum quantity of 15% diethyl ether (DEE) and copper nano particles.

Multiple Regression based prediction of Low Heat Rejection engine performance parameters

The machine learning task of multiple regressions is carried out in this section. The machine learning pipeline is followed to do this. The pipeline is shown in figure 3 below.

The operational parameters data of the medium grade LHR engine are obtained by conducting the experiment with recommended and optimum settings of these characteristics. The exploratory data analysis (EDA) (Tukey, (1977) is then performed. The descriptive statistics of the dataset is tabulated below.

The above tabulated summary statistics reveal that:

1. Most values of injection timing are concentrated around 27 and 30 indicating a bimodal distribution.
2. The injection pressure data ranges from 190 to 270 with significant variation.
3. Temperature data is narrowly spread around the mean.
4. Exhaust Gas Temperature (EGT) data is wide ranged which suggests that there is significant variation.
5. Volumetric Efficiency (VE) data is slightly spread around the mean indicating moderate variation.
6. Coolant Load (CL) data ranges from 2.4 to 4.5, with values slightly spread around the mean.
7. BTE data indicates slight spread, with most values between 4.31 and 5.94.
8. BMEP values are closely packed around the mean, indicating less variation.
9. BP shows moderate variation, with values from 50.92 to 62.23.

The correlation map showing the positive and negative correlations between the operational parameters and performance parameters is shown in figure 4 below.

The key insights drawn from the above heatmap are given below.

- Injection timing and Temperature have a very strong positive correlation (0.89), suggesting that as injection timing increases, temperature also increases.
- EGT and Coolant Load are almost perfectly correlated (0.99), indicating that as one increases, the other also increases.

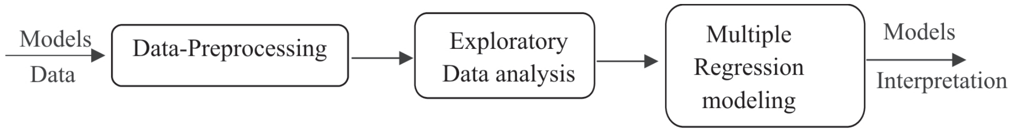


Fig. 3. Machine Learning Pipeline

Table 4. Descriptive Statistics of the operational parameters data

Operational Parameters	Mean	std	min	25%	50%	75%	max
Injection timing	28.384615	1.556624	27.000000	27.000000	27.000000	30.000000	30.000000
Injection pressure	226.923077	34.492660	190.000000	190.000000	230.000000	270.000000	270.000000
Temperature	31.076923	1.272238	29.000000	30.000000	31.000000	32.000000	33.000000
EGT	358.461538	61.114122	280.000000	320.000000	340.000000	400.000000	460.000000
VE	79.000000	1.791182	75.500000	78.000000	79.500000	80.000000	82.000000
CL	3.192308	0.687340	2.400000	2.800000	3.000000	3.400000	4.500000
BTE	5.060154	0.690146	4.310000	4.336000	5.110000	5.908000	5.935000
BMEP	8.700000	0.389444	8.100000	8.400000	8.700000	9.000000	9.300000
BP	55.437308	3.398770	50.922000	52.441000	54.922000	58.349000	62.234000

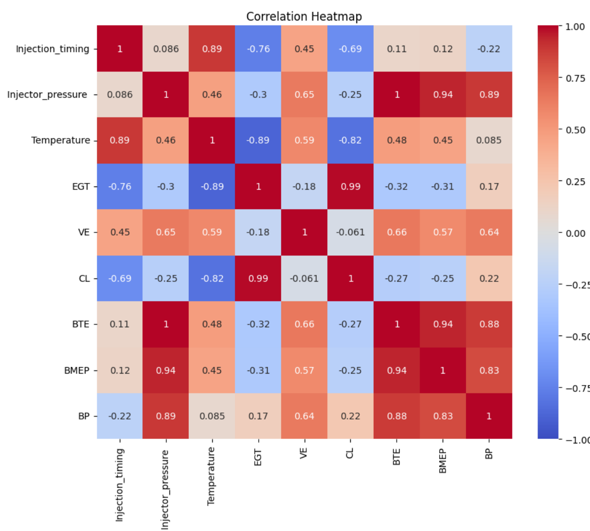


Fig. 4. Correlation Heat Map

- Injection pressure is highly correlated with BMEP (0.94) and BP (0.89), implying that changes in injection pressure significantly affect these parameters.
- Temperature shows a strong negative correlation with EGT (-0.89) and Coolant Load (-0.82), suggesting that higher temperatures are associated with lower values of these parameters.
- VE has moderate positive correlations with Injection pressure (0.65), Temperature (0.59), BMEP (0.57), and BP (0.64), indicating its influence on these variables.
- BTE and BMEP are strongly correlated with Injection pressure and BP, highlighting their interconnectedness in the engine performance metrics.

The final assumption to examine to perform regression as the downstream task in data analysis is Autocorrelation among the variables in the data. The test to examine autocorrelation is Durbin-Watson test (Durbin and Watson, 1950). For the given data the Durbin-Watson test statistic is approximately 2.57. This value suggests that there is no evidence of autocorrelation in the residuals of the upcoming regression models. This indicates that the residuals are fairly independent which is a good sign for the validity of the regression models.

The important operational parameters that are useful for regression task are identified by performing correlation heatmap analysis (Rajendran, *et al.*, 2023). It is observed that the important features for analyzing BTE performance parameter are BMEP, BP, Temperature, and Injection pressure. The important features for analyzing BMEP performance parameter is only BTE. The important features for analyzing BP performance parameter are BTE and Volumetric Efficiency. The important features bar plots for BTE, BMEP and BP are shown in Figure 5 below.

These features are fed to the multiple regression machine learning algorithm. Multiple Regression analysis is a technique to formulate mathematical relationship between some independent variables (response or operational parameters) and a dependent variable (predictor or performance parameter). It is an extension of simple linear regression. The model will produce regression coefficients that quantify the contribution of each independent variable to the overall prediction.

Multiple regressions is useful in engine research and development because it allows engineers to

- Understand the relative importance of different operational parameters on engine performance.
- Develop predictive models that can be used to optimize engine designs and operating conditions.
- Identify potential interactions between engine

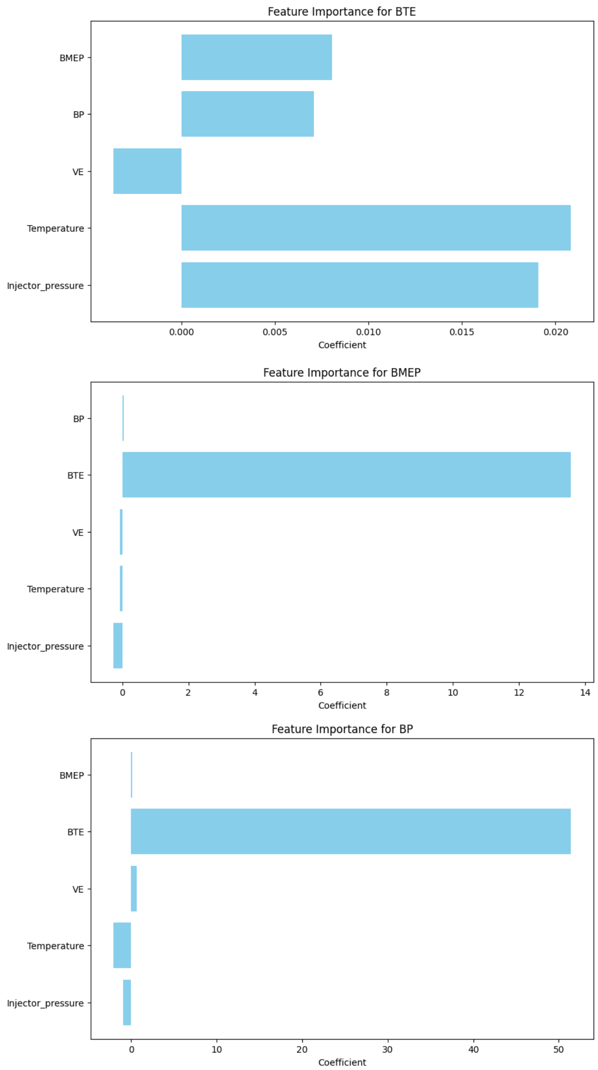


Fig. 5. Important Features for Regression

parameters that may affect performance in complex ways.

The mathematical model of multiple regression is given below.

$$Y = a_0 + a_1x_1 + a_2x_2 + \dots + a_nx_n \quad (1)$$

Where, Y is a dependent variable, a_0 to a_n is equation parameters for linear relation and x_1 to x_n are independent variables. The quality of fit of the linear model to a given set of observed data can be judged by using the coefficient of determination, i.e. R^2.

The multiple regression BTE model relating the operational parameters is given in the below equation.

BTE = 0.300 + (0.010 * Injection_timing) + (0.020 * Injector_pressure) + (-0.002 * Temperature) + (-0.000 * EGT) + (-0.000 * VE) + (0.000 * CL) .. (2)

The visualization of the model showing the relationship between actual and predicted BTE is shown in figure 6 below.

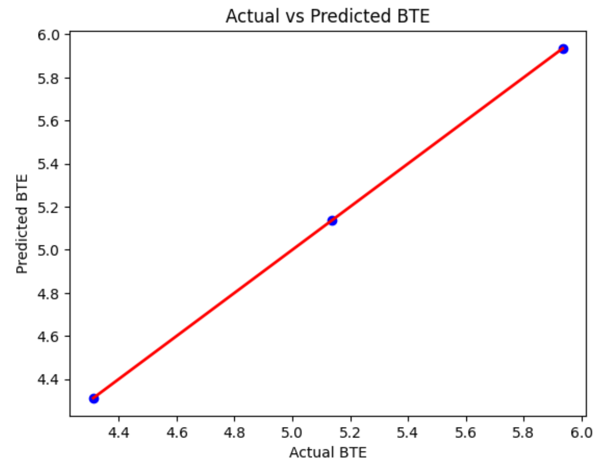


Fig. 6. BTE Multiple Regression Model

The multiple regression BMEP model relating the operational parameters is given in the below equation.

BMEP = 9.460 + (0.018 * Injection_timing) + (0.014 * Injector_pressure) + (0.284 * Temperature) + (-0.005 * EGT) + (-0.181 * VE) + (0.911 * CL) .. (3)

The visualization of the model showing the relationship between actual and predicted BMEP is shown in Figure 7 below.

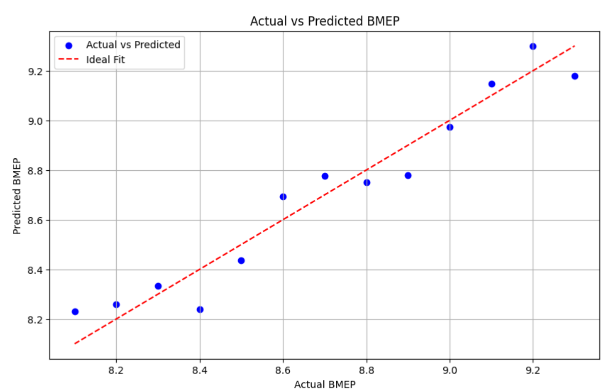


Fig. 7. BMEP Multiple Regression Model

The multiple regression BP model relating the operational parameters is given in the below equation.

BP = 10.000 + (0.200 * Injection_timing) + (0.100 * Injector_pressure) + (-0.050 * Temperature) + (0.030 * EGT) + (0.100 * VE) + (-0.010 * CL) .. (4)

The visualization of the model showing the relationship between actual and predicted BP is shown in Figure 8 below.

The R^2 and MSE values of the above three multiple regression models after validating are tabulated below.

Table 5. R^2 and MSE values

Multiple Regression Model	R^2	MSE
BTE	1	5.259072701473412e-31
BMEP	0.939	0.008507146268173806
BP	1	1.9418114590055676e-28

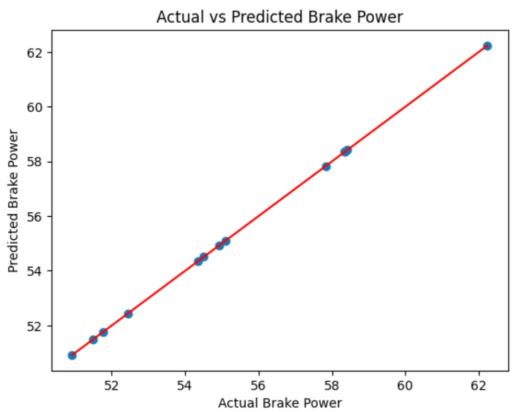


Fig. 8. BP Multiple Regression Model

It is observed from the R^2 values from the above table that all the three multiple regression models are able to capture all the relevant relationships between operational parameters and the corresponding performance parameter. Also it is observed from MSE values that all the three multiple regression models are highly accurate in providing the predictions.

Results and Discussion

Performance Parameters

Figure 9(a) shows the variation of brake thermal efficiency (BTE) with brake mean effective pressure for conventional engine (CE) for algae oil blended with 15% DEE and nano particles.

BTE increased up to 80% of the load and beyond that load, it decreased with test fuels. This is due to increase of fuel conversion efficiency, mechanical efficiency and oxygen-fuel ratio up to 80% of the full load and reduction of the same beyond 80% of the load. The optimum injection timing (OIT) is the timing, at which the efficiency of the engine with test fuels is greater or equal to diesel operation on conventional engine. The recommended injection timing (RIT) is the timing specified by the manufacturer. (27°bTDC). At RIT, the performance of algae oil (AO) with CE deteriorated due to lower calorific value and high viscosity of the fuel. However, at 31°bTDC, performance improved due to atomization characteristics of the test fuel. Hence the optimum injection timing for CE with algae oil was found to be 31°bTDC.

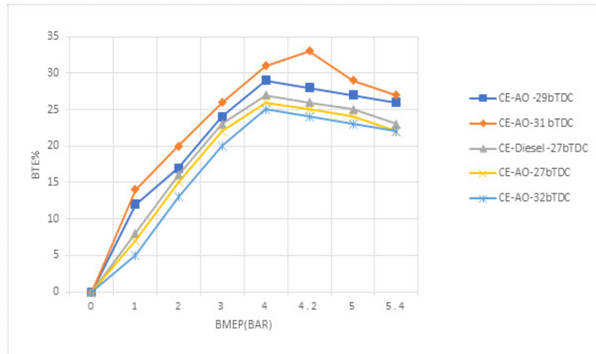


Fig. 9(a). Variation of BTE with BMEP for conventional engine (CE) with algae oil Blended with DEE and Copper Nano Particles (AO).

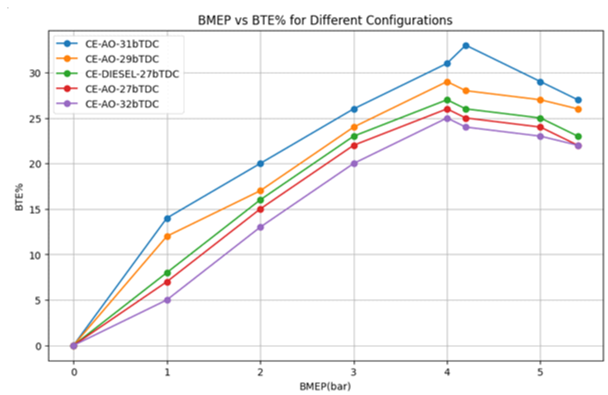


Fig. 9(b). Variation of BTE with BMEP for conventional engine (CE) with algae oil Blended with DEE and Copper Nano Particles (AO) for Machine learning Model

Figure 10 (a) shows the variation of brake thermal efficiency (BTE) with brake mean effective pressure for LHR engine for algae oil (AO) blended with 15% DEE and nano particles. The optimum injection timing for LHR engine was observed to be 30°bTDC, which was lower than CE due to hot combustion chamber provided by LHR engine.

From the Figure 11(a), it was noticed that CE with

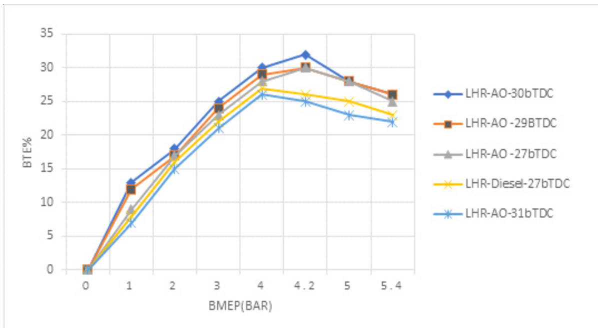


Fig. 10(a). Variation of BTE with BMEP for LHR engine with algae oil Blended with DEE and Copper Nano Particles (AO)

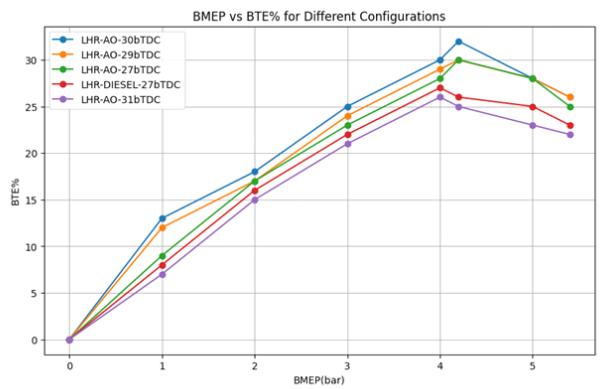


Fig. 10(b). Variation of BTE with BMEP for LHR engine with algae oil (AO) blended with DEE and Copper Nano Particlesfor Machine Learning Model

Algae oil at the recommended injection timing recorded marginally higher exhaust gas temperature (EGT) at all loads compared with CE with pure diesel operation. Lower heat release rates and retarded heat release associated with high specific energy consumption caused increase in exhaust gas temperature (EGT) in CE. Ignition delay in the CE with different operating conditions of Algae oil increased the duration of the burning phase.

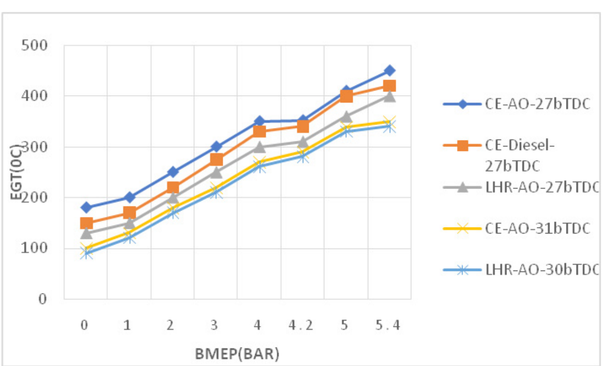


Fig. 11(a). Variation of (EGT) with (BMEP) in conventional engine (CE) and low heat rejection (LHR) engine at recommend injection timing and optimized injection timings with Algae oil blended with DEE and Copper Nano Particles operation

LHR engine recorded lower value of exhaust gas temperature (EGT) when compared with CE with Algae oil operation. This was due to reduction of ignition delay in the hot environment with the provision of the insulation in the LHR engine, which caused the gases expanded in the cylinder giving higher work output and lower heat rejection. This showed that the performance improved with LHR engine over CE with Algae oil operation. The value of exhaust gas temperature at peak load decreased with advancing of injection timing and with increase of injector opening pressure in both versions of the engine with Algae oil.

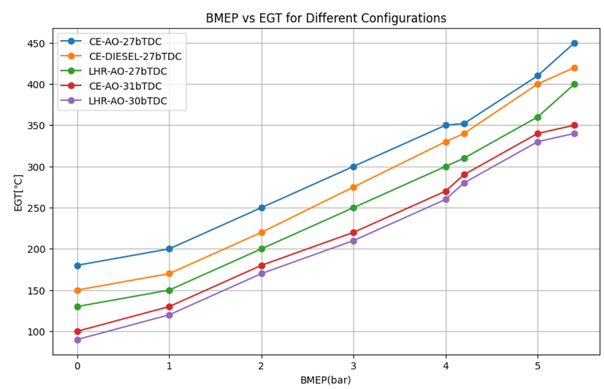


Fig. 11(b). Variation of (EGT) with (BMEP) in conventional engine (CE) and low heat rejection (LHR) engine at recommend injection timing and optimized injection timings with Algae oil blended with DEE and Copper Nano Particles operationfor Machine Learning Model

From Figure 12(a), it was noticed that volumetric efficiency (VE) decreased with an increase of BMEP in both versions of the engine with test fuels. This was due to increase of gas temperature with the load. At the recommended injection timing, VE in the both versions of the engine with Algae oil operation decreased at all loads when compared with CE with pure diesel operation. This was due to increase of deposits with Algae oil operation with CE. With LHR engine, this was due increase of temperature of incoming charge in the hot environment created with the provision of insulation, causing reduction in the density and hence the quantity of air with

LHR engine.VE increased marginally in CE and LHR engine at optimized injection timings when compared with recommended injection timing with A. This was due to decrease of un-burnt fuel fraction in the cylinder leading to increase in VE in CE and reduction of gas temperatures with LHR engine. VE decreased relatively by 6.5% with LHR engine at its optimized injection timing when compared with pure diesel operation on CE.

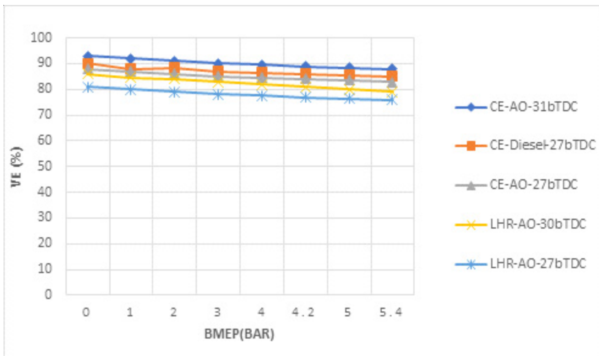


Fig. 12(a). Variation of (VE) with BMEP in CE and LHR engine at recommend injection timing and optimized injection timings with Algae oil Blended with DEE and Copper Nano Particles operation.

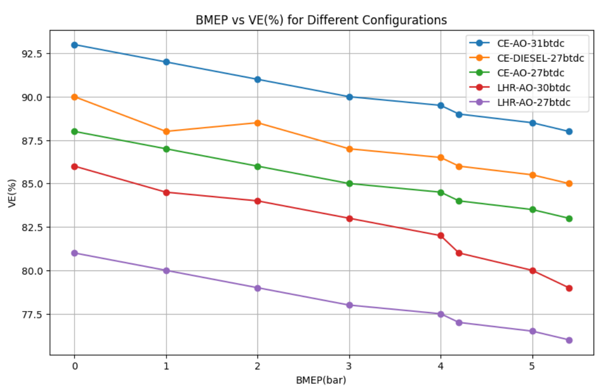


Fig. 12(b). Variation of (VE) with BMEP in CE and LHR engine at recommend injection timing and optimized injection timings with Algae oil Blended with DEE and Copper Nano Particlesoperation for Machine Learning Model

Figure 13(a) indicate that that coolant load (CL) increased with BMEP in both versions of the engine with test fuels. However, coolant load (CL) reduced with LHR version of the engine with Algae oil operation when compared with CE with pure diesel operation

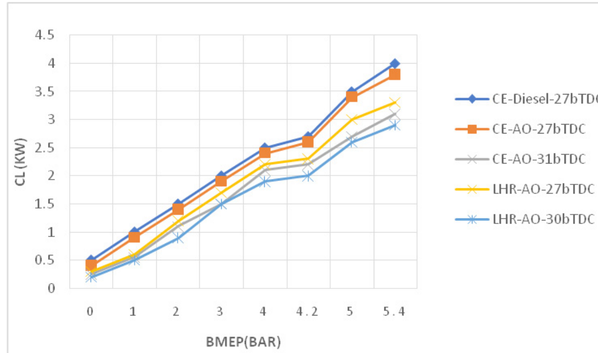


Fig. 13(a). Variation of (CL) with BMEP in both versions of the engine at recommended and optimized injection timings with Algae oil blended with DEE and Copper Nano Particles operation.

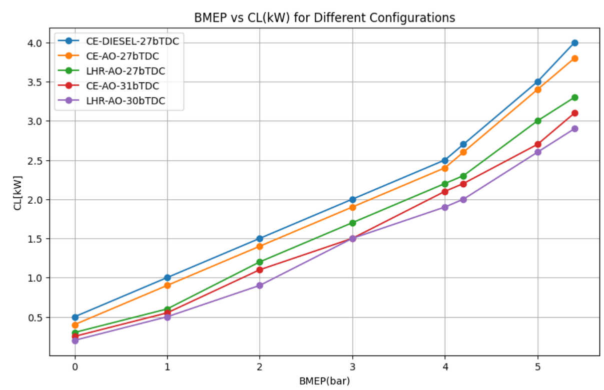


Fig. 13(b). Variation of (CL) with BMEP in both versions of the engine at recommended and optimized injection timings with Algae oil Blended with DEE and Copper Nano Particles operation for Machine Learning Model

Heat output was properly utilized and hence thermal efficiency increased and heat loss to coolant decreased with effective thermal insulation with LHR engine However, CL increased with CE with Algae oil operation in comparison with pure diesel operation on CE. This was due to concentration of un-burnt fuel at the walls of combustion chamber. CL decreased with advanced injection timing with both versions of the engine with Algae oil operation. This was due to improved air fuel ratios and reduction of gas temperatures.

The comparison between R^2 and MSE values of this present work with the existing works are tabulated below.

Bold face indicates best performance by the corresponding algorithm

From the above table both Sanjeevannavar, M. B. *et*

Table 6. Comparison between R^2 and MSE values

Work	Machine Learning Algorithms	R^2	MSE
Tanmaya Agarwal *et al.* (2020)	Multiple Regression	Not reported	6.37% (for BTE)
Mallesh *et al.* (2023)	Linear Regression, XG Boost, Random Forest Regressor, Decision Tree Regressor	1 (for all algorithms and all for BTE)	4.587, 0.248, 0.441, 0.727 (all for BTE)
Present Work	Multiple Regression	1 (for BTE), 0.939 (for BMEP), 1 (for BP) (for BTE),	5.259072701473412e-31 0.008507146268173806 (for BMEP), 1.9418114590055676e-28 (for BP)

al. (2023) and the Present Work report an R^2 of 1 for BTE, indicating perfect prediction. The Present Work also reports an R^2 of 1 for BP, suggesting perfect prediction. For BMEP, the Present Work reports an R^2 of 0.939, which is still very high and indicates a good fit.

Also, for BTE, the Present Work reports an MSE of 5.259072701473412e-31, which is significantly lower than any MSE reported by Sanjeevannavar, M.B. *et al.* (2023), indicating a much better model performance. For BMEP, the Present Work reports an MSE of 0.008507146268173806, which is not directly comparable with previous works but suggests high accuracy. For BP, the Present Work reports an MSE of 1.9418114590055676e-28, indicating excellent model performance.

This shows that the present work outperforms previous studies in terms of MSE, indicating higher model accuracy for predicting BTE, BMEP, and BP. These better performing multiple regression models are helpfulto optimize medium grade LHR engine operation and reduce the unplanned downtime.

Conclusion

A comprehensive analysis of the performance parameters of a Low Heat Rejection (LHR) engine using multiple regressions is carried out successfully. This study focused on predicting the performance parameters of the engine, including Brake Thermal Efficiency (BTE), Brake Mean Effective Pressure (BMEP), and Brake Power (BP).

The observed optimum settings and the performance parameter values after conducting the experiments from the physical medium grade LHR engine are: optimum injection timing for CE was 31°bTDC, (before top dead centre) while, it was 30°bTDC with LHR engine. Peak brake thermal efficiency increased by 12.5%, at peak load operation-brake specific energy consumption decreased by 5.5%, exhaust gas temperature decreased by 85°C, volumetric efficiency decreased by 6%, coolant load decreased by 25%.

The authors used machine learning techniques and developed multiple regression models to estimate the performance of the engine based on its operational parameters and performance parameters data as part of simulation. The regression models achieved high accuracy, as indicated by high R-squared values for BTE and BP, and a very low Mean Square Error value for BMEP. This work also discussed the related works on the integration of machine learning techniques with LHR engines. Overall, the findings suggest that machine learning can optimize LHR engine operation, improve engine efficiency, and reduce downtime. These findings are satisfying with the physical performance parameters optimum settings and values.

Conflict of Interest- None

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