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Machine Learning Analysis Of CRDI Engine Performance Using Mahua Oil Blends Of Biodiesel

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This study examines the optimization of a Common Rail Direct Injection (CRDI) engine operating on a mahua oil and diesel blend to improve engine performance and minimize emissions. Response Surface Methodology (RSM) and Analysis of Variance (ANOVA) were utilized to evaluate the impacts of three principal input parameters: blend %, compression ratio, and injection pressure, including their interactions and higher-order effects. The findings indicated that compression ratio and injection pressure are critical parameters, exhibiting substantial nonlinear impacts on Brake Thermal Efficiency (BTE), Carbon Monoxide (CO), and Nitrogen Oxides (NOx) emissions. The blend %, while having a negligible direct effect, strongly interacted with other parameters to influence the engine's performance. The model demonstrated exceptional accuracy, with a R^2 value of 0.9952, signifying that it accounted for nearly 99% of the variability in the response. This study emphasizes the necessity of concurrently tweaking several engine parameters to attain peak efficiency and low emissions when utilizing biofuel blends. The results provide significant insights into the viability of mahua oil as a sustainable fuel for diesel engines, facilitating a transition to cleaner and more efficient biofuel use in contemporary engines.

Keywords: Mahua, ANOVA, Biodiesel, Efficiency, Optimization

1. Introduction

Sustainable alternatives to traditional fossil fuels are being sought after more and more due to the growing worldwide demand for energy and the associated environmental problems. Biofuels made from plants that aren't edible have risen to the top of the list because of the positive impact they could have on lowering emissions of greenhouse gases and our reliance on fossil fuels [1]. An attractive biodiesel alternative is mahua oil, which is produced from the Madhuca indica tree's seeds and is especially suitable for areas where the plant is abundantly available [2]. Because of its high calorific value and high cetane number, it is an ideal fuel to mix with diesel for use in compression ignition engines [3]. The timing, pressure, and duration of fuel injection are all variables that modern diesel engines, particularly those with Common Rail Direct Injection (CRDI) systems, provide more control over. Engine performance, fuel economy, and emissions can all be greatly enhanced with this level of control [4-5]. While there have been a lot of studies on CRDI engines running on biodiesel blends, very few have looked at how to get the most out of the engine's input parameters when running on a combination of diesel and mahua oil. For the purpose of assessing the viability of using biofuels in commercial diesel engines, it is essential to comprehend how these blends impact emissions, specifically CO and NOx, as well as important performance metrics like Brake Thermal Efficiency (BTE) [6-7]. A renewable and eco-friendly substitute for diesel made from petroleum, biodiesel is produced from animal fats and vegetable oils and has been the subject of extensive research. There is hope that biofuels can lessen the negative effects of fossil fuels on the environment, provide energy security, and cut down on emissions of carbon dioxide (CO_2) [1]. Mahua, jatropha, and neem are non-edible oils that have been recognized as potential feedstocks because of their accessibility, affordability, and lack of competition with food crops [2]. One of these, mahua oil, is making waves due to its diesel engine compatibility. Mahaua oil is an excellent choice for biodiesel production because to its high cetane numbers and viscosity, as shown in multiple tests [3]. Mahua oil is a potential alternative fuel since it can be successfully transesterified to make biodiesel with characteristics that are similar to diesel, according to researchers [4]. Diesel engines run better on mahua oil or diesel-oil mixtures, according to a plethora of research. According to Babu and Devaraj [5], CI engines that used mahua biodiesel blends had better combustion characteristics, such as a greater brake thermal efficiency (BTE) than those that used pure diesel. On the other hand, because biodiesel blends often contain more oxygen, they tend to produce more nitrogen oxides (NOx) emissions [6]. When blended with diesel at a 20% ratio (B20), mahua oil biodiesel blends provide the best performance in terms of engine efficiency and emissions, according to research by Venkateswara Rao et al. [7]. In contrast to clean diesel, they found reduced emissions of carbon monoxide (CO) and hydrocarbons (HC), but slightly increased emissions of nitrogen oxides (NOx). Some studies have looked at how biodiesel mixes affect engine wear and lubrication, whereas others have concentrated on the former. Using mahua biodiesel, for example, was associated with better lubrication qualities and less engine wear, according to research by Udayakumar et al. [8]. This shows that biodiesel may help CI engines in more ways than one, including performance and lowering maintenance costs. Fuel injection parameters in CRDI engines may be fine-tuned for maximum performance and minimum emissions thanks to the increased control they enable [9]. Optimizing input parameters like injection time, fuel pressure, and duration is crucial for achieving the full benefits of biodiesel mixes, especially with the growing use of CRDI technology. To find the best engine performance settings, several optimization methods have been used, such as Genetic Algorithms (GA), Response Surface Methodology (RSM), and the Taguchi approach [10]. Research has shown that when using biodiesel, engine output may be dramatically altered by modifying injection pressure and timing. By adjusting the injection timing and pressure, Pandian et al. [11] were able to significantly boost BTE while decreasing CO and NOx emissions from a CRDI engine that ran on a jatropha oil blend. Bhaskar et al. [12] optimized CRDI engine parameters for a jatropha-diesel blend using RSM, striking an ideal compromise between performance and pollution reduction; this study is identical to the one described here. Gopal et al. [13] optimized a CRDI engine that ran on mahua biodiesel using the Taguchi method, which is unique to mahua oil. They found that BTE improved by

12% and that emissions of NOx and CO were reduced. Their observation was that optimization approaches may be further refined to achieve even better outcomes. In order to get the most out of biodiesel engines, these experiments show that fuel injection management is crucial. Reduced emissions of carbon-based pollutants are the main reason biodiesel is good for the environment. Diesel engines can potentially reduce particulate matter (PM), carbon monoxide (CO), and unburned hydrocarbons (HC) with biodiesel blends, especially those made from non-edible sources like mahua oil [14]. Biodiesel blends can reduce CO emissions by as much as 50% compared to pure diesel, according to research by Narayana and Ramesh [15]. Reduced HC emissions are another benefit of using biodiesel, thanks to its high oxygen content, which encourages more complete combustion. Many academics have attempted to find a solution to the problem of increased NOx emissions caused by biodiesel use. According to research, this problem can be reduced by adjusting the injection timing, optimizing the fuel blends, and utilizing exhaust gas recirculation (EGR). Research by Channappagoudra et al. [16] demonstrated that biodiesel-fueled engines might have their NOx emissions reduced without sacrificing efficiency by improving CRDI engine characteristics. Although there is an increasing amount of research on biodiesel, particularly mahua oil, in CI and CRDI engines, very little is known about how to optimize CRDI engine characteristics for mahua oil-diesel blends. Parameter optimization's combined impacts on performance and emissions have been understudied compared to their individual effects. In addition, there is a lack of data on the effects of various injection settings on the mahua oil-related BTE, CO, and NOx emission balance. To address these knowledge gaps, this study optimizes the CRDI engine's input parameters for a mahua oil-diesel blend and assesses how these factors affect the engine's performance and emissions. To help achieve the larger objective of increasing the practicality of biofuels for use in diesel engines, this study use state-of-the-art optimization methods to determine the optimal operating conditions that maximize BTE while decreasing CO and NOx emissions.

2. Methodology

2.1. Blend preparation

The amalgamation of mahua oil with diesel necessitates particular procedures to guarantee the stability and efficacy of the resultant fuel mixture in diesel engines. Mahua oil is generally derived from the seeds of the Madhuca indica tree either mechanical pressing or solvent extraction. This unrefined mahua oil requires pre-treatment techniques prior to blending with diesel to eliminate contaminants, decrease viscosity, and enhance its overall fuel characteristics. Upon preparation of the pre-treated mahua oil, it is amalgamated with standard diesel fuel to generate the requisite fuel combination. The blending ratio generally fluctuates based on the application and research aims. Figure 1 illustrated the transesterified biodiesel.

Fig. 1. Transesterified biodiesel

2.2. Machine learning models

Machine Learning (ML) has emerged as a potent instrument for enhancing engine performance, especially in intricate systems such as CRDI (Common Rail Direct Injection) engines, where multiple parameters affect engine efficiency and emissions. In optimizing a CRDI engine utilizing a mahua oil and diesel blend, machine learning can elucidate complex relationships between input parameters (e.g., injection timing, fuel pressure, air-fuel ratio) and output responses, including Brake Thermal Efficiency (BTE), Carbon Monoxide (CO) emissions, and Nitrogen Oxides (NOx) emissions. Utilizing machine learning techniques enhances the efficiency and accuracy of the engine optimization process, diminishing dependence on conventional trial-and-error approaches and facilitating the analysis of extensive datasets. The application of machine learning in this context enhances fuel efficiency, diminishes emissions, and elevates overall engine performance by determining the optimal parameter combinations. Table 1 presents the design of experiments (DOE) for the prediction of response variables. The displayed central composite design was utilized to implement machine learning models.

Table 1. Design of experiments (DOE) of optimization of engine parameters

Blend (%)	Compression ratio	Injection pressure (bar)	BTE (%)	NOx (ppm)	CO (vol.%)
10	21	800	26	532	0.17
10	19	800	26	532	0.171
5	21	1000	26.1	572	0.19
10	19	600	26	560	0.1745

20	20	800	24.3	578	0.18
5	21	1000	26.1	570	0.1964
10	20	800	26.8	566	0.1695
15	19	600	25.6	567	0.1817
15	21	600	26.4	572	0.1746
10	20	800	26.8	562	0.1695
0	20	800	25.8	559	0.1849
10	20	800	26.8	532	0.1695
5	19	1000	25.9	552	0.1821
10	20	800	26.8	532	0.1695
15	21	1000	26	580	0.2027
15	20	800	26.4	532	0.1772
5	19	1000	25.9	542	0.1821
10	20	1000	26.4	558	0.1839
10	21	1000	26.4	567	0.1944
5	19	600	25.9	540	0.1776
15	21	600	26.4	567	0.1746
5	20	800	26.6	532	0.1721
5	19	600	25.9	549	0.1776
5	21	80	26	565	0.2133
15	19	1000	26.6	551	0.1892
10	20	400	25.9	552	0.1781
15	19	1000	26.6	565	0.1892
10	21	600	27.2	553	0.1678
5	18	800	25.7	545	0.1824
10	22	800	27.3	575	0.1875

3. Results and Discussion

3.1. ANOVA studies using machine learning

Analysis of variance is conducted to examine the discrepancies between actual and projected outcomes of response variables relative to the specified input components. The correlation coefficient R^2 and the corrected R^2 are presented in Tables 2, 3, and 4. R-squared values indicated the relationship between input and response variables. The calculated R-squared and adjusted R-squared values demonstrated a robust association between input and output variables.

3.1.1. Variance studies of Brake Thermal Efficiency (BTE), NOx emissions and CO emissions

Table 2. ANOVA of BTE

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	9.41	19	0.4951	108.71	< 0.0001	significant
A-Blend	0.0005	1	0.0005	0.1142	0.7424	
B-Compression ratio	0.344	1	0.344	75.53	< 0.0001	
C-Injection pressure	0.3828	1	0.3828	84.05	< 0.0001	
AB	0.5793	1	0.5793	127.18	< 0.0001	
AC	0.5376	1	0.5376	118.04	< 0.0001	
BC	0.4554	1	0.4554	100	< 0.0001	
A^2	4.34	1	4.34	952.83	< 0.0001	
B^2	0.9578	1	0.9578	210.3	< 0.0001	
C^2	0.6011	1	0.6011	131.98	< 0.0001	
Residual	0.0455	10	0.0046			
Lack of Fit	0.0455	2	0.0228			
Pure Error	0	8	0			
Cor Total	9.45	29				
R^2 = 0.9952	**R^2 Adj. = 0.9860**					

Table 3. ANOVA of NOx emissions

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	4056.78	9	450.75	3.12	0.0164	significant
A-Blendd	959.7	1	959.7	6.64	0.018	
B-Compression ratio	625.09	1	625.09	4.32	0.0507	
C-Injection pressure	269.09	1	269.09	1.86	0.1876	

AB	0.777	1	0.777	0.0054	0.9423	
AC	256.1	1	256.1	1.77	0.1982	
BC	591.75	1	591.75	4.09	0.0566	
A^2	978.45	1	978.45	6.77	0.0171	
B^2	526.71	1	526.71	3.64	0.0708	
C^2	1012.72	1	1012.72	7	0.0155	
Residual	2891.52	20	144.58			
Lack of Fit	1656.52	12	138.04	0.8942	0.5844	not significant
Pure Error	1235	8	154.38			
Cor Total	6948.3	29				
R^2 = 0.7839	**R^2 Adj. = 0.8166**					

Table 3. ANOVA of CO emissions

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	0.0034	19	0.0002	63.8	< 0.0001	significant
A-Blend	0	1	0	5.79	0.0369	
B-Compression ratio	8.74E-06	1	8.74E-06	3.15	0.1063	
C-Injection pressure	0	1	0	17.7	0.0018	
AB	0	1	0	5.15	0.0466	
AC	8.83E-06	1	8.83E-06	3.18	0.1048	
BC	0	1	0	14.77	0.0033	
A^2	0.0002	1	0.0002	88.26	< 0.0001	
B^2	4.49E-07	1	4.49E-07	0.1619	0.6959	
C^2	0	1	0	4.31	0.0646	
Residual	0	10	2.78E-06			
Lack of Fit	7.27E-06	2	3.63E-06	1.42	0.2968	not significant
Pure Error	0	8	2.56E-06			
Cor Total	0.0034	29				
R^2 = 0.9918	**R^2 Adj. = 0.9763**					

Table 2, 3, and 4 illustrate that the engine optimization study reveals low p-values and high F-values for most variables, including B-Compression ratio, C-Injection pressure, and their interactions, indicating their substantial significance. They significantly influence the fluctuations noted in BTE, CO, and NOx emissions. The higher-order terms (e.g., A^2, B^2) exhibit elevated F-values and diminished p-values, signifying that nonlinear effects are essential in ascertaining the engine's performance.

3.2. Regression plots using machine learning algorithms

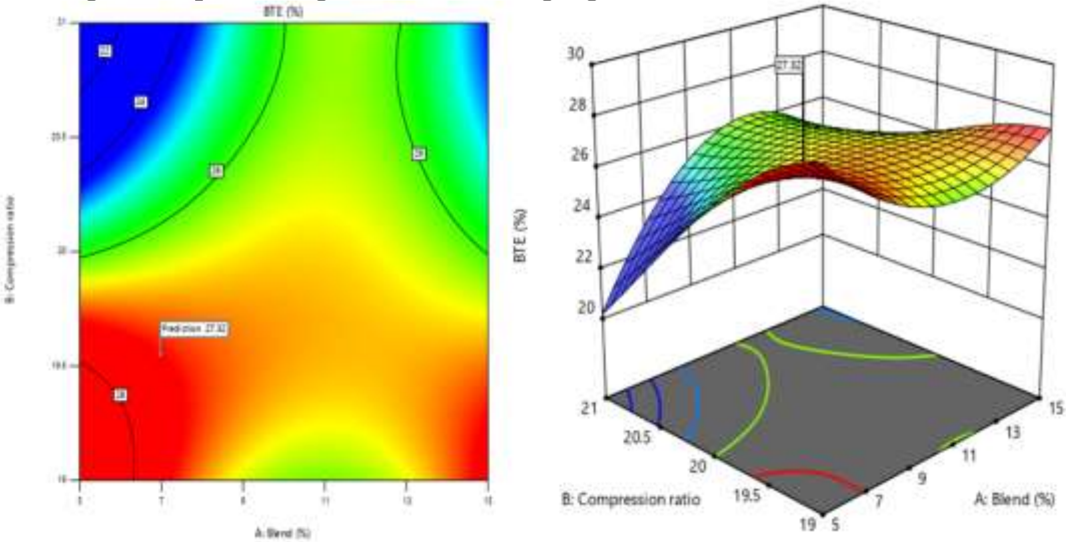


Fig. 2. Regression contour plots of BTE

The integrated findings from the contour and 3D surface plots indicate that a blend ratio of roughly 7% mahua oil and a compression ratio of about 19.5 yield the ideal circumstances for maximizing Brake Thermal Efficiency, as illustrated in Fig. 2. This result illustrates the essential equilibrium between the fuel mixture and engine settings that optimizes efficiency in CRDI engines. It underscores the necessity of optimizing both blend ratios and engine operating parameters to attain optimal performance when utilizing biofuels such as mahua oil. The BTE forecast of 27.32% is noteworthy, as it suggests that mahua oil-diesel blends can operate effectively in diesel engines when utilized with precisely calibrated parameters. This research contributes to the expanding evidence base that endorses biofuels for mitigating the environmental impact of diesel engines while preserving high efficiency.

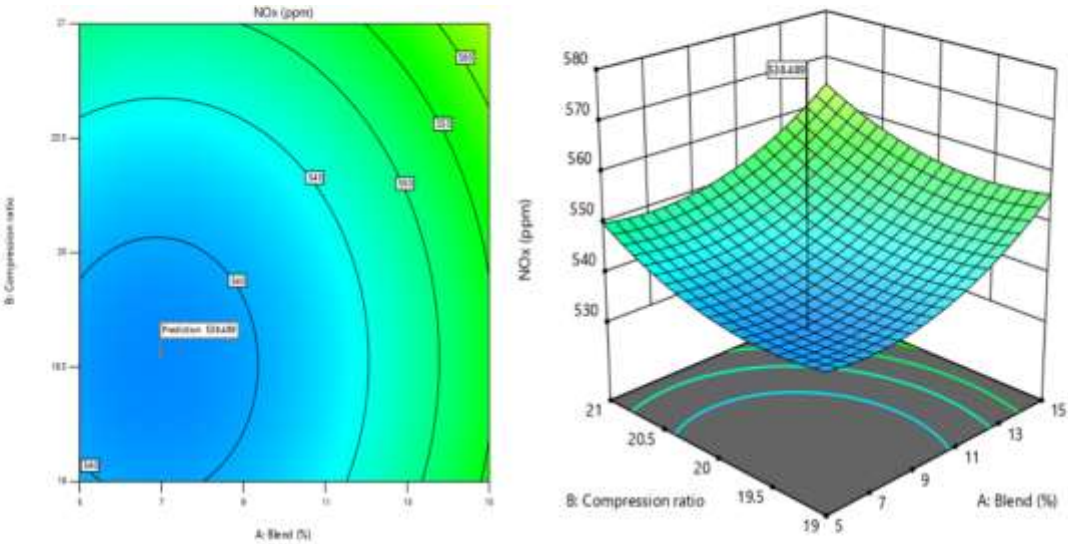


Fig. 3. Regression contour plots of NOx emissions

Both the contour and 3D surface plots in Fig. 3 clearly indicate that the best blend percentage and compression ratio for minimizing NOx emissions are roughly 7% mahua oil blend and a compression ratio of around 19.5. Operating the engine within these settings ensures that NOx emissions remain at their minimum level (538.49 ppm) while still employing a biofuel blend. This discovery is significant as NOx emissions pose a substantial environmental issue, and their reduction is a priority in engine optimization, especially with biodiesel mixes such as mahua oil. The results emphasize the necessity of meticulously adjusting fuel blend ratios with engine operating conditions to attain emission reductions while maintaining engine performance.

The contour and 3D surface plots in Figure 4 clearly indicate that the ideal blend percentage and compression ratio for reducing CO emissions is approximately 7% mahua oil blend and a compression ratio of 19.5. This discovery is significant as CO emissions result from incomplete combustion; reducing them enhances engine efficiency and mitigates environmental damage. The figures indicate that minor adjustments in blend percentages or compression ratios do not substantially impact CO emissions, suggesting a degree of flexibility in these parameters without considerable increases in CO generation. The ideal point yields the minimum attainable CO emission within the evaluated range, rendering it the most advantageous configuration for diminishing carbon monoxide output in this biofuel blend.

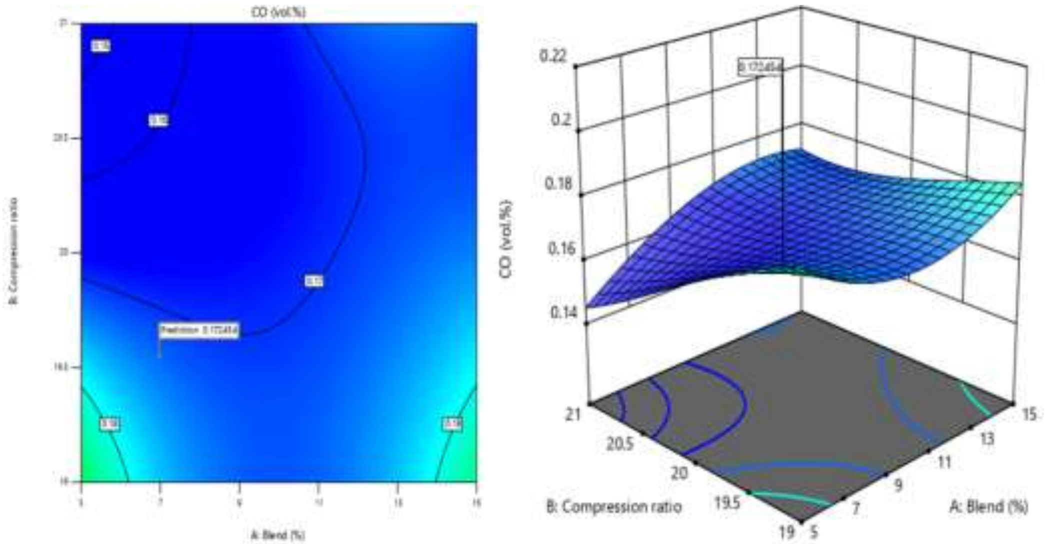
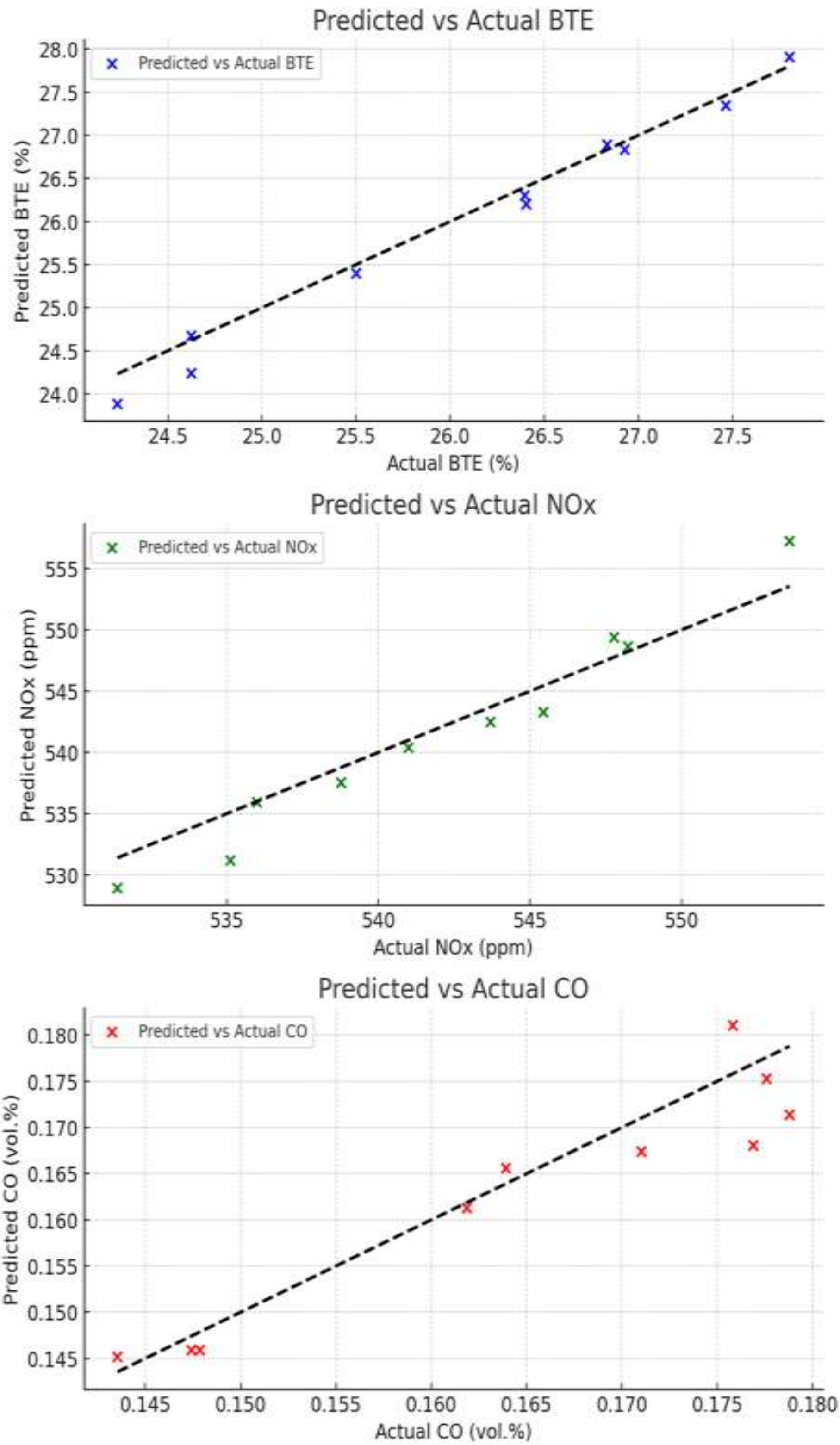


Fig. 4. Regression contour plots of CO emissions

3.3. Machine learning based predictions of response variables

Figure 5 illustrates the comparison between projected and actual values for three outputs: Brake Thermal Efficiency (BTE), Nitrogen Oxides (NOx), and Carbon Monoxide (CO). Each plot juxtaposes the model's anticipated values against the actual measured values, illustrating the degree of alignment between forecasts and reality. The dashed line signifies the optimal scenario in which the predicted values coincide with the actual values. The BTE figure demonstrated a strong correlation between the predicted and actual values, signifying that the model forecasts BTE with commendable precision. The NOx plot demonstrated that the anticipated NOx values closely align with the actual values, signifying a dependable forecast for NOx emissions. Additionally, the CO Plot's projected CO levels exhibit a satisfactory correlation with the actual values, but with slightly greater variance relative to the BTE and NOx plots.


Predicted vs Actual BTE
Predicted vs Actual BTE
Predicted BTE (%)
Actual BTE (%)
28.0
27.5
27.0
26.5
26.0
25.5
25.0
24.5
24.0
24.5
25.0
25.5
26.0
26.5
27.0
27.5
Predicted vs Actual NOx
Predicted vs Actual NOx
Predicted NOx (ppm)
Actual NOx (ppm)
555
550
545
540
535
530
535
540
545
550
Predicted vs Actual CO
Predicted vs Actual CO
Predicted CO (vol.%)
Actual CO (vol.%)
0.180
0.175
0.170
0.165
0.160
0.155
0.150
0.145
0.145
0.150
0.155
0.160
0.165
0.170
0.175
0.180

4. Conclusion

This research employed an extensive statistical analysis, utilizing ANOVA and Response Surface Methodology (RSM), to enhance the performance of a CRDI engine functioning with a mixture of mahua oil and diesel. The inquiry uncovered multiple significant discoveries:

- The compression ratio (B) and injection pressure (C) are critical parameters affecting engine performance, evidenced by their very low p-values (< 0.0001) and elevated F-values. These characteristics significantly influenced Brake Thermal Efficiency (BTE), Carbon Monoxide (CO), and Nitrogen Oxides (NOx) emissions.

- The interaction effects between factors, specifically AB (Blend and Compression Ratio) and AC (Blend and Injection Pressure), were notably strong. These interactions underscore the intricate links among engine settings and output responses, suggesting that maximizing a single parameter in isolation may not produce optimal results.

- The research revealed significant nonlinear effects, including the quadratic terms (A^2, B^2, C^2) and cubic terms (A^3, B^3, C^3). The major higher-order impacts must be considered for the accurate optimization of engine performance and emissions control. The blend % (A) did not considerably influence engine performance on its own; nevertheless, its interaction with other parameters and its nonlinear effects (A^2) were crucial. This indicates that the blend ratio must be meticulously tuned alongside other engine parameters to attain optimal performance.

- The model had exceptional accuracy, evidenced by a R^2 value of 0.9952 and an adjusted R^2 of 0.9860, signifying that it accounted for almost 99% of the variance in the response data. The minimal residual values and the negligible lack of fit further validated the model's reliability.

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