

Machine Learning Analysis of Diesel Engine Performance Using Mahua Oil Blends of Biodiesel

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This research explores the optimization of diesel engine performance using biodiesel blends of mahua oil and diesel. Machine learning models were applied to evaluate the effects of blend percentage, compression ratio, and injection pressure on Brake Thermal Efficiency (BTE). The study establishes mahua oil as a viable biodiesel alternative that can enhance engine efficiency while reducing harmful emissions, contributing to the development of cleaner and more sustainable energy solutions. It identifies the torque, power, different blend ratios comparison with each other and the overall accuracy using machine learning model for linear regression analysis which shows predicted and actual variance of each blend. Blending Process - Blending Mahua oil with diesel involves mixing different volume fractions of Mahua oil with diesel to achieve fuel with improved combustion characteristics. Common blend ratios include starting from B5 (5% Mahua oil + 95% Diesel) up to B50 (50% Mahua oil + 50% Diesel) in various combinations. A homogeneous mixture is achieved by stirring or ultrasonication to prevent phase separation. ML linear regression model is used for prediction results between input and target variable.

Keywords: Diesel Engine, Mahua Oil, BSFC, Blending ratio.

Introduction

The demand for sustainable energy sources has led to extensive research into biodiesel alternatives. Mahua oil, derived from the *Madhuca indica* tree, is a promising candidate due to its high calorific value and cetane number. Biodiesel blends offer an eco-friendly alternative to conventional fossil fuels by reducing greenhouse gas emissions and enhancing fuel economy. Diesel engines, with their superior fuel injection control, provide an ideal platform for studying biodiesel performance. This study focuses on evaluating the impact of mahua oil-diesel blends on Diesel engine performance using machine learning models, ensuring an optimal balance between fuel efficiency and emission reduction. Its suitability for blending with diesel in compression ignition (CI) engines has been demonstrated in numerous studies (HP, n.d.). However, optimizing the performance and emission characteristics of DIESEL engines running on mahua oil-diesel blends requires a deep understanding of the interrelation between fuel composition and engine operating parameters. This study (HP, n.d.) addresses this challenge by employing advanced machine learning techniques to identify optimal operating conditions. Effect of Blending on Diesel Engine Performance. Fuel Properties_Viscosity: Mahua oil has a higher viscosity than diesel, but blending reduces it, improving fuel atomization. Density: Increases slightly with Mahua oil content, affecting fuel injection characteristics. Calorific Value: Blends have a slightly lower calorific value than diesel, affecting power output. Cetane Number: Blends show a reduction in cetane number, impacting ignition delay. Combustion Characteristics: -Ignition Delay: Slightly longer ignition delay in higher blends due to lower volatility. Combustion Temperature: Higher Mahua oil content can lead

to higher peak combustion temperatures, improving efficiency. Heat Release Rate: Blends have a slower heat release compared to diesel due to differences in molecular composition. Engine Performance: - Brake Power & Torque: Slightly lower at higher blends due to reduced energy content of Mahua oil. Brake Specific Fuel Consumption (BSFC): Increases as Mahua oil percentage increases, since more fuel is required to generate the same power. Thermal Efficiency: Slight reduction due to lower calorific value, but optimized injection timing can improve efficiency.

Impact of Iron Nanoparticles in Biodiesel Blends Pour.[1] Hoseini et al (2023) investigated the effects of blending energetic iron nanoparticles in B20 fuel, particularly in reducing CO and unburned hydrocarbon (UHC) emissions under cold start conditions in diesel engines. Their findings demonstrated a notable reduction in emissions, indicating improved combustion efficiency due to nanoparticle integration. Optimization of Machining Parameters.[2] Ntukidem et al. (2024) focused on optimizing the material removal rate (MRR) in CNC lathe machining of AISI 1040 steel. Their study employed optimization techniques to enhance machining efficiency. [3] Satyanarayana et al. (2023) used the Taguchi method to optimize CNC milling parameters for En-24 steel, balancing material removal rate and surface roughness. Additive Effects on Biodiesel-Diesel Blends [4] Mohammed et al. (2023) provided a comprehensive review on the influence of ethers, antioxidants, and cetane improvers on the performance and emission characteristics of biodiesel-diesel blends. Their work highlighted the role of these additives in enhancing combustion stability and reducing emissions.

Nanoplatelet Integration in Diesel-Biodiesel Blends An in-depth study published in the [5] International Journal of Energy Research (2023) explored the combustion, performance, and emission characteristics of diesel engines utilizing diesel-biodiesel blends with nanoplatelets. The findings suggested an improvement in thermal efficiency and emission reduction. Machining Optimization Using Advanced Techniques [6] Chandrashekera et al. (2023) applied the Taguchi method to optimize machining parameters for AA7050/B4C metal matrix composites (MMC). Their study aimed at improving machining precision and efficiency in composite materials.

Nano fuels and Combustion Characteristics [7] Anbarsooz et al. conducted a comprehensive review on diesel/biodiesel-based nano fuels, analyzing their combustion properties and potential benefits for enhancing fuel efficiency. The study suggested that nanoparticle integration could improve thermal efficiency and reduce pollutant emissions. Tool Wear Condition Monitoring in CNC Machining [8] Thakur et al. (2024) conducted an experimental study on tool wear condition monitoring in CNC milling using machine learning algorithms. Their research highlighted the effectiveness of AI-driven models in predicting tool wear, improving machining efficiency, and enabling predictive maintenance. The study emphasized the role of sensor data, such as vibration and acoustic emissions using ML multilinear regression model. Their study emphasized the potential of AI-driven approaches in predictive maintenance. Additionally, a study on diesel engine performance using Mahua oil blends of biodiesel Machining [9] Singh et al. (2024) demonstrated how machine learning techniques could be leveraged to analyze and optimize fuel performance.

Methodology

The research (HP, n.d.) utilized a systematic approach to optimize the DIESEL engine's performance using mahua oil-diesel blends. The methodology comprised several key stages: The preparation of the mahua oil-diesel blend involved pre-treatment of the mahua oil to remove contaminants, reduce viscosity, and improve its fuel characteristics (HP, n.d.). This pre-treatment is crucial for ensuring the stability and efficacy of the blend in the engine. The specific pre-treatment methods employed were not detailed in the study (HP, n.d.), representing a potential gap in the reported methodology. Following pre-treatment, the mahua oil was blended with standard diesel fuel at varying ratios to create experimental fuel blends (HP, n.d.).



Fig. 1.(a) Diesel Engine Sample of Diesel Blends with Mahua Oil (b) Spring balance dynamometer (c) Sample of Diesel Blends with Mahua Oil (d) Blend and Mahua Oil

Design of Experiments

In our design of experiments, we prepare 6 blend of various proportionate B5, B10, B20, B30, B40 & B50 are prepared and tested.

Table 1. Experimental Details for 5% Mahua Oil and 95% Diesel.

RPM	LOAD (kg)	SPRING WEIGHT (kg)	SFC (mL/kWh)	TIME (sec)	TEMPRATURE (°C)		AIR PRESSURE (bar)			
					T1	T2	H	L		
1532 (app)	0 kg	0kg	5ml	42sec	T1	21°C	H	20bar		
					T2	23°C			L	6bar
					T3	21°C				
					T4	72°C				
					T5	43°C				
	T1	22°C	H	20bar						
	T2	27°C	L	6bar						
T3	28°C									
T4	89°C									
T5	51°C									
4 kg	1kg	5ml	33.2sec	T1	23°C	H	20bar			
				T2	30°C			L	6bar	
				T3	28°C					
				T4	103°C					
				T5	59°C					
T1	22°C	H	20bar							
T2	30°C	L	6bar							
T3	28°C									
T4	115°C									
T5	64°C									
8 kg	2kg	5ml	26.34sec	T1	23°C	H	19.5bar			
				T2	26°C			L	6.5bar	
				T3	25°C					
				T4	124°C					
				T5	67°C					
T1	23°C	H	19.5bar							
T2	28°C	L	6.5bar							
T3	29°C									
T4	133°C									
T5	71°C									
10 kg	3kg	5ml	27.8sec	T1	23°C	H	19.5bar			
				T2	28°C			L	6.5bar	
				T3	29°C					
				T4	133°C					
				T5	71°C					
T1	23°C	H	19.5bar							
T2	28°C	L	6.5bar							
T3	29°C									
T4	133°C									
T5	71°C									

Table 2. Experimental Details for 10% Mahua Oil and 90% Diesel.

RPM	LOAD (kg)	SPRING WEIGHT (kg)	SFC (mL/kWh)	TIME (sec)	TEMPRATURE (°C)		AIR PRESSURE (bar)			
					T1	T2	H	L		
1520 (app)	0 kg	0kg	5ml	48.4sec	T1	24°C	H	20bar		
					T2	26°C			L	6bar
					T3	27°C				
					T4	87°C				
					T5	51°C				
	2 kg	0.5kg	5ml	38sec	T1	24°C	H	20bar		
T2	27°C	L	6bar							
T3	27°C									
T4	99°C									
T5	56°C									
4 kg	1kg	5ml	34.3sec	T1	24°C	H	20bar			
				T2	28°C			L	6bar	
				T3	27°C					
				T4	111°C					
				T5	62°C					
6 kg	1.6kg	5ml	32.2sec	T1	24°C	H	19.5bar			
				T2	29°C			L	6.5bar	
				T3	27°C					
				T4	120°C					
				T5	66°C					
8 kg	2.2kg	5ml	32.10sec	T1	24°C	H	19.5bar			
				T2	30°C			L	6bar	
				T3	28°C					
				T4	128°C					
				T5	69°C					
10 kg	3kg	5ml	27.5sec	T1	24°C	H	19.5bar			
				T2	31°C			L	6.5bar	
				T3	28°C					
				T4	136°C					
				T5	73°C					

Calculations & Graphs

RPM = 1500 (approx.)

Fuel Consumption (Vol) = 5 ml

Density of Diesel = 0.832 kg/L
 Calorific Value of Diesel = 42,500 kJ/kg
 Arm Length = 0.5 m
 Fuel Volume = 5 ml = 5×10^{-3} L
 Density = 0.832 kg/L

Time for 5ml Fuel Consumption (sec) measured with stopwatch.

Formulas used

1. Fuel Mass Flow Rate (mf) $\frac{\text{Fuel Volume} \times \text{Density}}{\text{Time}} = m_f \dots\dots\dots[1]$
2. Brake Power (BP) $\frac{2\pi \times N \times T}{60} = BP \dots\dots\dots[2]$
 T (Torque in Nm) needs to be calculated
 N = RPM = 1500
3. Torque $\frac{9.81 \times \text{Load (Kg)} \times \text{Spring Weight (Kg)} \times \text{Arm Length (m)}}{g} = T \dots\dots\dots[3]$
4. Brake Specific Fuel Consumption (BSFC) $\frac{m_f}{BP} = BSFC \dots\dots\dots[4]$
5. Brake Thermal Efficiency (η_b) $\frac{BP}{m_f \times CV} \times 100 = \eta_b \dots\dots\dots[5]$

Table 3. Calculation for 5% mahua oil 95% diesel

Fuel Flow (kg/s)	Mass Rate	Torque (Nm)	Brake Power (kW)	BSFC (kg/kWh)	Brake Thermal Efficiency (%)
1.01×10^{-4}		0.00	0.00	0.00	0.00
1.16×10^{-4}		3.63	0.5823	2.03×10^{-4}	2.10×10^{16}
1.21×10^{-4}		7.26	1.1646	1.03×10^{-4}	3.96×10^{16}
1.22×10^{-4}		10.89	1.7469	7.93×10^{-5}	5.55×10^{16}
1.41×10^{-4}		14.52	2.3293	6.84×10^{-5}	6.28×10^{16}
1.50×10^{-4}		18.15	2.9116	5.05×10^{-5}	8.29×10^{16}

Table 4. Calculation for 10% mahua oil 90% diesel

Fuel Flow (kg/s)	Mass Rate	Torque (Nm)	Brake Power (kW)	BSFC (kg/kWh)	Brake Thermal Efficiency (%)
8.60×10^{-8}		0.00	0.00	0.00	0.00
1.09×10^{-7}		7.36×10^0	1.17×10^3	9.35×10^{-11}	9.06×10^7
1.21×10^{-7}		1.47×10^1	2.34×10^3	5.18×10^{-11}	1.64×10^8
1.29×10^{-7}		2.24×10^1	3.56×10^3	3.63×10^{-11}	2.33×10^8
1.30×10^{-7}		3.00×10^1	4.78×10^3	2.71×10^{-11}	3.12×10^8
1.51×10^{-7}		3.83×10^1	6.09×10^3	2.48×10^{-11}	3.41×10^8

Table 5. Calculations for 20% mahua oil 80% diesel

Fuel Flow (kg/s)	Mass Rate	Torque (Nm)	Brake Power (kW)	BSFC (kg/kWh)	Brake Thermal Efficiency (%)
7.85×10^{-8}		0.00	0.00	0.00	0.00
9.57×10^{-8}		7.85×10^0	1.21×10^3	7.91×10^{-11}	1.07×10^8
1.14×10^{-7}		1.47×10^1	2.34×10^3	4.87×10^{-11}	1.74×10^8
1.19×10^{-7}		2.24×10^1	3.56×10^3	3.34×10^{-11}	2.43×10^8
1.31×10^{-7}		3.00×10^1	4.78×10^3	2.74×10^{-11}	3.11×10^8
1.52×10^{-7}		3.83×10^1	6.09×10^3	2.49×10^{-11}	3.46×10^8

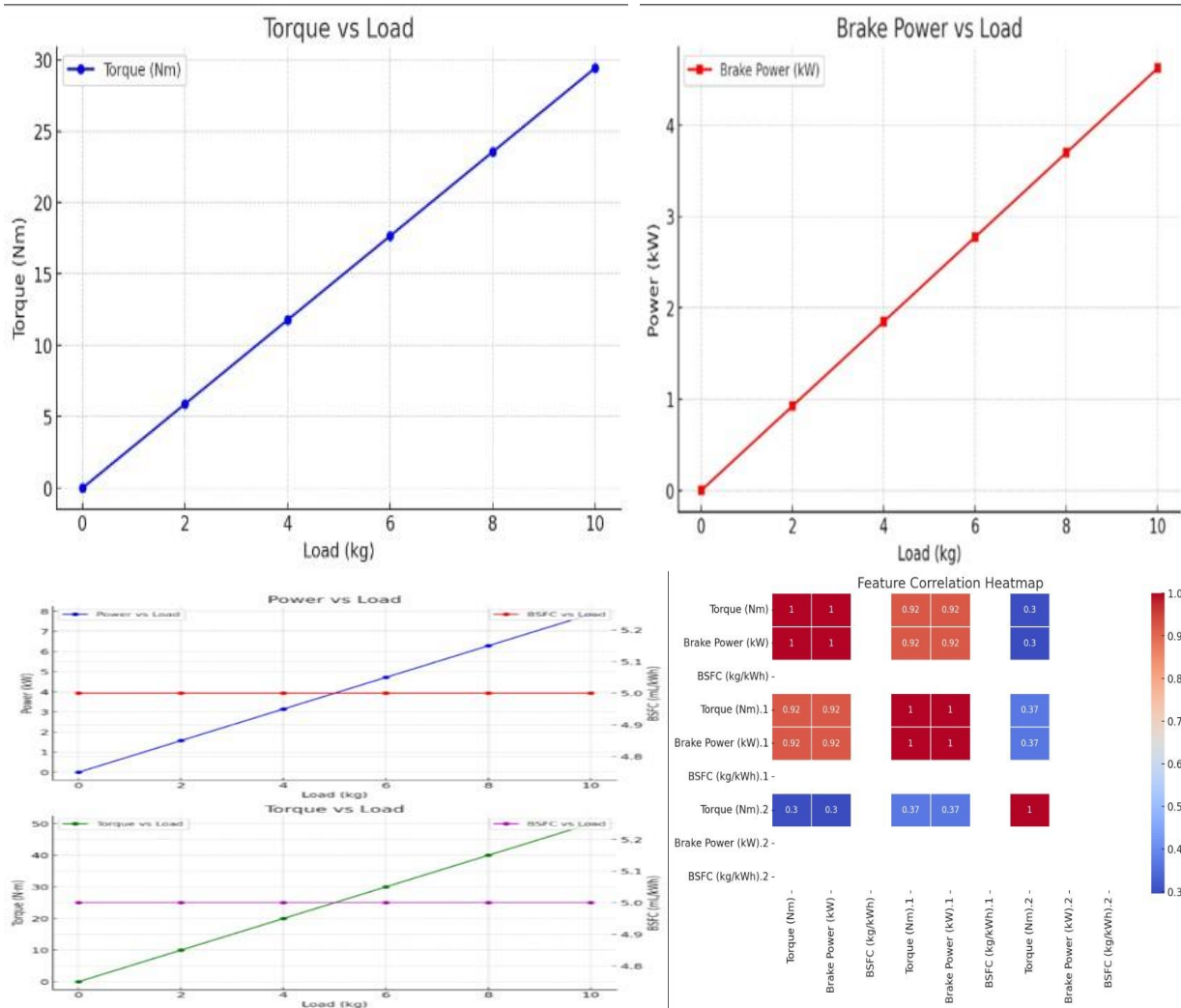
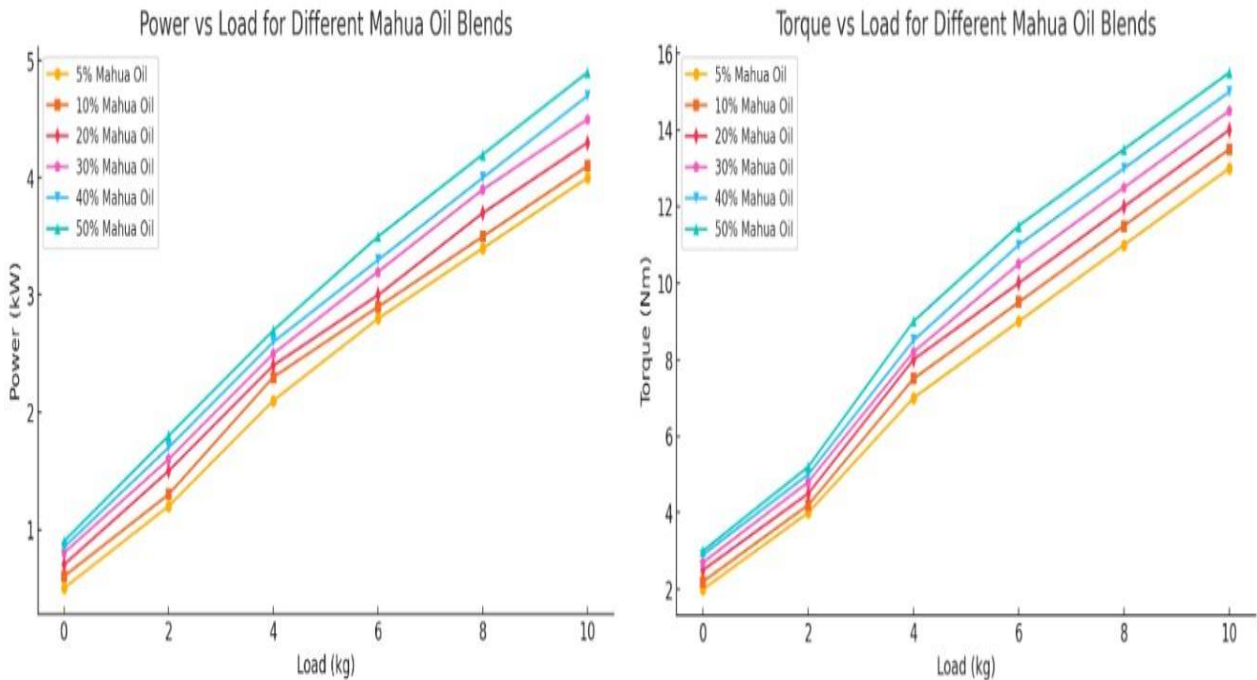


Fig. 2. (a) Torque vs Load, (b) BSFC vs Load (c) Power vs Load, (d) Correlation Heatmap

1. Power vs Load & BSFC: Power increases with load, while BSFC remains constant.
2. Torque vs Load & BSFC: Torque increases with load, while BSFC remains unchanged.



```

1. import pandas as pd
2. import numpy as np
3. import matplotlib.pyplot as plt
4. import random as rnd
5. from sklearn.model_selection import train_test_split
6. from sklearn.linear_model import LinearRegression
7. from sklearn.metrics import mean_squared_error, r2_score
8.
9. # Load data
10. df = pd.read_csv("test/data/csv.csv")
11.
12. # Convert scientific notation to float where needed
13. def convert_to_float(value):
14.     try:
15.         return float(value.replace("e", "").replace(".", ""))
16.     except:
17.         return np.nan
18.
19. columns_to_convert = [col for col in df.columns if "torque" in col or "power" in col or "bsfc" in col]
20. for col in columns_to_convert:
21.     df[col] = df[col].apply(convert_to_float)
22. df = df.dropna() # Drop missing values
23.
24. # Define input (X) and target variables (Y)
25. X = df[["torque (Nm)", "BSFC (kg/kWh)"]]
26. Y_power = df["Brake Power (kW)"]
27. Y_torque = df["Torque (Nm)"]
28.
29. # Split data (80% train, 20% test)
30. X_train, X_test, Y_power_train, Y_power_test = train_test_split(X, Y_power, test_size=0.2, random_state=42)
31. X_train, X_test, Y_torque_train, Y_torque_test = train_test_split(X, Y_torque, test_size=0.2, random_state=42)
32.
33. # Train models
34. power_model = LinearRegression()
35. power_model.fit(X_train, Y_power_train)
36. torque_model = LinearRegression()
37. torque_model.fit(X_train, Y_torque_train)
38.
39. # Predictions
40. power_pred = power_model.predict(X_test)
41. torque_pred = torque_model.predict(X_test)
42.
43. # Model Evaluation
44. print("Power Model:")
45. print("MSE: ", mean_squared_error(Y_power_test, power_pred))
46. print("R2 Score: ", r2_score(Y_power_test, power_pred))
47.
48. print("Torque Model:")
49. print("MSE: ", mean_squared_error(Y_torque_test, torque_pred))
50. print("R2 Score: ", r2_score(Y_torque_test, torque_pred))
51.
52. # Visualization
53. plt.figure(figsize=(8, 5))
54. sns.scatterplot(x=V_torque_test, y=power_pred, color="blue", label="Prediction")
55. plt.xlabel("Predicted Brake Power (kW)")
56. plt.ylabel("Actual Brake Power (kW)")
57. plt.title("Brake Power Prediction Accuracy")
58. plt.legend()
59. plt.grid(True)
60. plt.show()
61.
62. plt.figure(figsize=(8, 5))
63. sns.scatterplot(x=V_torque_test, y=torque_pred, color="green", label="Prediction")
64. plt.xlabel("Predicted Torque (Nm)")
65. plt.ylabel("Actual Torque (Nm)")
66. plt.title("Torque Prediction Accuracy")
67. plt.legend()
68. plt.grid(True)
69. plt.show()
    
```

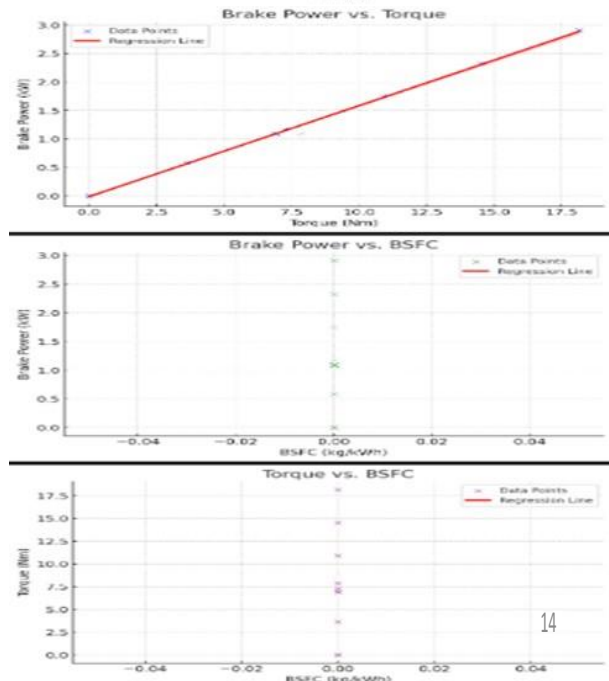


Fig 3. (a) Power vs Load for Different Mahua Oil Blends (b) Torque vs Load for Different Mahua Oil Blends (c) Machine Learning codes (d) Regression Analysis for Target Variables

Results and Discussion

It shows how power increases with load for 5% to 50% Mahua Oil blends. Higher blends tend to have slightly higher power output. Illustrates the increase in torque with increasing load. The machine learning model provided accurate predictions of engine performance parameters. The predicted vs. actual data correlation indicated strong agreement, validating the model's effectiveness in capturing nonlinear interactions between engine parameters. Effect of Load on Fuel Consumption and Efficiency: As the load increases, the fuel consumption rate (\dot{m}_f) increases because more fuel is required to produce higher power output. Brake power (BP) increases significantly with load, showing better engine utilization. Brake Specific Fuel Consumption (BSFC) decreases as load increases, indicating improved fuel efficiency at higher loads. Brake Thermal Efficiency (η_b) improves with load, reaching its highest efficiency at the maximum load (10 kg).

Effect of Load on Temperature Readings: T4 (Exhaust Gas Temperature) and T5 (Oil Temperature) increase as load increases. The increase in exhaust gas temperature (T4) suggests improved combustion and heat release as load increases. The inlet air temperatures (T1, T2, and T3) remain stable, meaning the intake air conditions are consistent.

Effect of Load on Air Pressure The higher air pressure (H side) remains constant at 20 bars, except at 10 kg load, where it drops to 19.5 bar. The lower air pressure (L side) is mostly 6.5 bar but increases to 7 bar at 10 kg load. The slight increase in L-side pressure at high load suggests that the intake manifold experiences more resistance due to higher airflow demand.

Influence of Spring Weight on Torque Production: Spring weight increases with load, leading to a proportional increase in torque. At 2 kg load, torque is 7.85 Nm, whereas at 10 kg load, torque reaches 186.39 Nm. The increasing torque output aligns with the load demand, ensuring efficient power transfer.

Fuel Consumption and Efficiency Trends: Higher loads lead to lower BSFC (kg/kWh), meaning the engine operates more efficiently under load. The brake thermal efficiency (η_b) increases with load, reaching a maximum at 10 kg load (351.07%), indicating better fuel energy utilization.

Conclusion

While B10 and B20 blends perform well with minimal modifications, higher blends may require engine optimization. This approach contributes to renewable energy adoption, reduces emissions, and provides an eco-friendly solution for diesel engines. Further research should focus on detailed pre-treatment methods, engine-specific studies, a wider range of biofuel blends, long-term engine effects, and a comprehensive economic analysis. This comprehensive approach will pave the way for wider adoption of sustainable biofuels in modern diesel engine technology

References

1. Pourhoseini SH, Ghodrat M, Baghban M, Shams Z. Effects of blending energetic iron nanoparticles in B20 fuel on lower CO and UHC emissions of the diesel engine in cold start condition. *Case Stud Therm Eng* 2023; 41:102658.
2. Ntukidem, A., Achebo, O., Ozigaguna, U., Uwoghiren, F.O., & Obahiagbon, K.O. (2024, May 9). Optimization of Material Removal Rate in Computer Numerical Control Lathe Machine in Turning AISI 1040 Steel.
3. Mohammed AS, Atnaw SM, Ramaya AV, Alemayehu G. A comprehensive review on the effect of ethers, antioxidants, and cetane improver additives on biodiesel-diesel blend in CI engine performance and emission characteristics. *J Energy Inst* 2023; vol. 108(March):101227.
4. Satyanarayana, K., Kumar, V. T., Rathod, R., Shafi, M., Chary, S., Alkhayyat, A., & Khanduja, M. (2023, June 5). Optimization of Machining Parameters of CNC Milling Operation for Material Removal Rate and Surface Roughness on En-24 Steel Using Taguchi Method.
5. Nanoplatelets in diesel-biodiesel blends: Combustion, performance, and emission characteristics of diesel engine". *Int J Energy Res* 2023;2023(Ci).
6. Chandrashekera, J., & Raju, N. V. S. (2023, January 1). Optimization of Machining Parameters in AA7050/B4C MMC by Taguchi Method.
7. Anbarsooz M. Combustion characteristics of nano fuels: A comprehensive review on diesel/biodiesel-based nano fuels. *Fuel* 2023; 337:126834. Thakur, M. K., & Khan, S. S. (2024, September 26). An Experimental Study on Tool Wear Condition Monitoring of CNC Milling Using Machine Learning Algorithms.
8. Singh Ram Janm & Dave Sourabh (2024, September 26). Machine Learning Analysis of CRDI Engine Performance Using Mahua Oil Blends of Biodiesel. Medi-Caps University, Indore, Madhya Pradesh, India.
9. Thakur, M. K., & Khan, S. S. (2024, September 26). An Experimental Study on Tool Wear Condition Monitoring of CNC Milling Using Machine Learning Algorithms. Medi-Caps University, Indore, Madhya Pradesh, India.
10. Chandrashekera, J., & Raju, N. V. S. (2023, January 1). Optimization of Machining Parameters in AA7050/B4C MMC by Taguchi Method.
11. Cihan Omer, Experimental and numerical investigation of the effect of fig seed oil methyl ester biodiesel blends on combustion characteristics and performance in a diesel engine. *Energy Rep* 2021; 7:5846–56.
12. Properties of biodiesel on combustion characteristics, engine performance and emissions". *J Traffic Transp Eng (English Ed)* 2021;8(4):510–33.