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Impact of metal oxides on thermal response of zirconia coated diesel engines fueled by Momordica biodiesel machine learning insights

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Biodiesel presents a favourable economic outlook and environmental benefits, yet it faces limitations such as diminished calorific value and suboptimal combustion characteristics. Recent research focuses on enhancing biodiesel performance using nanoparticles and thermal barrier coatings. This study investigates non-edible biodiesel from Momordica seed oil, tested on a single-cylinder diesel engine. Biodiesel blends of 10%, 20%, and 30% Momordica seed biodiesel were enhanced with cerium oxide nano additives at 45 ppm and evaluated using a partially stabilized zirconia-coated piston and cylinder liner. Additionally, machine learning (ML) algorithms, including Multiple Linear Regression (MLR), Gradient Boosting Regression (GBR), and Random Forest Regression (RF), were applied to predict thermal performance metrics using input parameters such as Fuel, Compression Ratio (CR), Load, and Peak Pressure (Bar). Among these, RF demonstrated the highest predictive accuracy, achieving the best R² values of 0.86 for Brake Thermal Efficiency (BTE) and 0.62 for Carbon Monoxide (CO) prediction, with the lowest Mean Absolute Error (MAE) of 1.30 and 2.88, respectively. These results highlight the potential of ML models in optimizing engine performance for sustainable energy systems across various engine types and fuel sources.

Keywords Momordica seed biodiesel, Partially stabilized zirconia, Hermal performance prediction, Multiple linear regression, Gradient boosting regression, Random forest regression, Energy efficiency

The depletion of renewable resources, reliance on fossil fuels, and increased oil prices necessitate searching for an alternate energy source. The combustion of fossil fuels produces greenhouse gases such as CO, HC, and NOx, contributing to global warming. A viable solution will be essential to mitigate the impacts of greenhouse emissions and avert global warming. The traditional diesel fuel used in diesel engines produces significantly higher levels of aromatics and sulfur, which contribute to environmental emissions[1]. Biofuels have been shown to enhance national energy security while being environmentally friendly, cost-effective, and producing lower emissions. The faith in biofuels as a means of growing their reliance on imported fossil fuels while supplementing their conventional energy supplies. Additionally, it meets the nation's enormous energy needs by using non-edible feedstocks. Additionally, ceramic coatings mitigate the detrimental consequences of wear, vibration, cooking, degradation, and oxidation. The coated engine improves the thermal performance of the brakes and reduces brake-specific fuel usage[2,38].

Thermally insulating the combustion chamber will produce less heat flow to the coolant and increased exhaust energy. Compared to a traditional CI engine, the semi-adiabatic engine achieves a weight and volume reduction of approximately 40%. The semi-adiabatic engine's compact size and powerful power-to-weight ratio dramatically decrease vehicle size and weight. Both inorganic and organic fuel additives have been used to

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address issues with biodiesel[3]. In addition, an additive makes better combustion efficiency and thereby decreases emissions. Physics can account for the fact that it provides fuel additives that enhance the combustion process of fossil fuels in combustion systems. Fuel nano-additives are mainly used to improve combustion efficiency and reduce toxic emissions in continuous and internal combustion systems[4].

Biodiesel may be produced using edible or non-edible oils. Cooking oils such as coconut, groundnut, soyabean, and sunflower were all tried. However, extracting biodiesel from vegetable oils may not be practicable because of the rising demand for edible oil, its high cost in nature, and other factors. In addition, the low volatility and high viscosity of vegetable oils are the key drawbacks when utilized as an energy source in a diesel engine. The high viscosity of vegetable oils impairs atomization, air-fuel mixture formation, and biodiesel evaporation. This results in abnormal combustion and increased smoke output[5]. In addition, vegetable oils' high viscosity introduces complications such as trouble starting the engine, variable ignition, and decreased thermal efficiency. Thus, it is determined that non-edible oil is a preferable alternative for biodiesel production as a substitute fuel. Using non-edible oils in biodiesel production is viewed as a feasible alternative to edible oils. Jatropha, Pongamia, rubber tree, mahua, and neem are the primary sources of non-edible oils. Non-edible oil resources attract considerable attention because they are widely accessible and efficiently farmed worldwide in many areas, particularly drylands and wastelands[3,6].

Nanoscience and nanotechnology advancements have allowed the fabrication, control, and characterization of energetic nanoscale materials. Because of their increasing surface area, nanomaterials are more potent than organic materials[7]. Another significant benefit of nanomaterials is their small scale, which eliminates the possibility of clogging in fuel injectors and filters, which is valid for micron-sized particles. The fuel droplets of all nano- and micron-scaled particles vary by size, concentration, and the shape of the base fluid. With higher energy densities of metals such as aluminum, the engine's power output is considerably increased, and emissions such as CO2, NOx, etc., are reduced. Surfactant was applied and sonicated to inhibit coagulation[8]. It demonstrated that n-decane settled within 10 min, while ethanol remained intact and in a suspension condition for more than 24 h, owing to ethanol's tendency to wet the molecule, forming a gel around it, and the vicious impact of ethanol. sorbitan oleate (2.5 wt%) was used as a surfactant to improve the stabilization and agglomeration of metal nanoparticles in n-alkane. the effect on exhaust emissions of a four-stroke diesel engine operating on biodiesel, using a vegetable oil-based additive with a metal additive[9].

Investigation simulated using hydrogen-blended fuels for slight efficiency and fuel consumption increases while drastically cutting CO and particulate matter emissions. Ignition delay was shortest with hydrogen-diethyl ether, while hydrogen-butanol produced the lowest CO2 emission (578.61 g/kWh) at CR 19.5, but NOx emissions were higher than diesel fuel[10]. Investigations were performed to evaluate MAME100, kapok oil KA100 and soybean oil SME100 biodiesel blends as substitutes for diesel fuels. When MAME20D80 and KA20D80 blends were investigated, reductions in BTE (by 1.5–2.0%) were detected while increases in SFC occurred, the emissions of NOx were reduced, 10–14.2%. SME20D80 emitted more CO2 (11.4%) than the other. All these blends show some moderate trade-offs in terms of sustainability[11].

Recent studies show the appraisal of incorporating nanoparticles in biodiesel blends to achieve better performance during engine operation and emission reduction. Srinivasa et al. evaluated graphene oxide (GO) and zinc oxide (ZnO) nanoparticles in a Mahua biodiesel blend (B20), showing that stability was enhanced and emissions were significantly reduced with dosage modification of surfactant. The injection pressure of 250 bar g saw a 4.24% increase in BTE and a reduction of BSFC by 3.59%, further reducing CO, unburned hydrocarbons, nitrogen oxides (NOx), and smoke opacity by 47.05%, 15.12%, 18.96%, and 37.09%, respectively[12]. Kiran Kavalli et al. synthesized green ZnO nanoparticles using cow dung as a catalyst for biodiesel production from waste frying oil. The resulting blend, B20-30 (B20 with 30 mg ZnO-GS), showed optimum BTE and BSFC with reduced emissions of greenhouse gases, demonstrating the efficiency of the green synthesis methods in producing ZnO nanoparticles[13].

Mofijur et al. reviewed the advantages of adding nanoparticle blends like CeO_2 and Al_2O_3 into biodiesel, observing a 12% increase in BTE and a decrease in emissions (CO by 60%, HC by 44%, smoke by 38%, and NOx by 30%). Similarly, Prabu et al. also investigated aluminum oxide nanoparticles in biodiesel. They found a consistent growth of 6% in BTE and significant emissions reductions, including a further drop of 33% in HC and 8% in CO at the optimized fuel injection timings. These studies observe together that there is an opportunity for the nanoparticle-improved biodiesel's alternative for sustainable and efficient energy solutions, wherein the design of specific nanoparticle formulations led to reduced emissions and improved combustion properties[7,14]. With cerium oxide (CeO2) nanoparticles, torque improved in diesel–tre pyrolysis oil blends, reduced bullock sales fat contents and reduced particulate emissions, although nitrogen oxide emission increased. The TO10D80 + NA100 ppm blend showed better performance and emissions when compared to diesel, clearly signifying its potential to be a cleaner fuel[15].

The test was conducted with a blend of palm biodiesel and ethanol, palm polyol and magnesium oxide. The additive increases the fuel efficiency of the engine, while the CO material drops due to excess air. Since the mixed diesel contains an ingredient, the temperature inside the tank during combustion is decreased, resulting in reduction in NOx emissions. The size and quantity effects of Al and $Al2O_3$ nanoparticles on the ignition properties were studied[16]. It has been shown that the ignition time has been reduced and the possibility of diesel ignition is increased. Thus it was concluded that improving heat and mass transfer properties of the fuel would reduce the time taken to evaporate droplets. The present investigation utilised the transesterification method to manufacture biodiesel from canola oil, refined palm stearin, and grape seed oil and evaluated each biodiesel's efficiency and emission characteristics in a CI engine. Additionally, the impact of nano-fuel additives was examined on each biodiesel fuel. The benefits of CeO_2 nanoparticles have led to their increased usage as a diesel fuel additive in other applications. It has been stated that nanoscale CeO_2 improves fuel combustion performance and reduces soot emissions[17].

Various researchers (Table 1.) have investigated metal oxide nanoparticles in biodiesel blends, emphasizing improved engine performance and emission reduction. Studies show that adding metal oxide nanoparticles like ZnO, CeO_2, and Al_2O_3 enhances combustion efficiency, increases BTE, and reduces CO, HC, and particulate matter emissions. Such biodiesel-nanoparticle fuels greatly minimize undesirable exhaust emissions, which have a late effect on NOx emission levels. Using nanoadditives improves fuel properties and. provides enhanced cleanliness during combustion, which has excellent potential towards sustainable diesel engine working.

The nano-sized CeO_2 particles are mixed with fuel to increase combustion. CeO_2 nanoparticles may be included in a fuel additive composition mixed with fuel to form a fuel composition, or they may be included in the fuel composition itself. If nano CeO_2 improves combustion, incomplete combustion products such as monoxide and hydrocarbons can be reduced[36]. The test findings indicate that using nanoscale CeO_2 decreased CO emissions compared to fuels that did not contain CeO_2. Energy is a critical component of every nation's financial development and one of the primary variables defining existence's importance[25,26].

The performance characteristics of the biodiesel from Momordica seed oil were studied on a single-cylinder diesel engine in pure biodiesel blends 10%, 20%, and 30%- added with cerium oxide nanoparticles at 45 ppm in an innovative engine test setup of partially stabilized zirconia-coated piston and cylinder liner. The engine performance characteristics were compared while keeping the coated/uncoated engine conditions in view. The study revealed the considerable advantage of the nano-enhanced biodiesel blends. The innovation of this work consists in the application of machine learning (ML) algorithms-Multiple Linear Regression (MLR), Gradient Boosting Regression (GBR), and Random Forest Regression (RF) for predicting the thermal performance metrics based on the input of given parameters like fuel type, compression ratio, load, and injection pressure. The application of the ML models optimizes performance. It provides a scalable framework for analysis of future engine configurations using new or alternative fuels, thereby providing the modus operand for advanced data-based sustainable energy systems[14,22,37].

Materials and methods

Since the oil collected from Momordica charantia seeds is non-edible, it may be used to make biodiesel, fragrances, and other compounds. Extract raw oil and convert it into biodiesel. In that, 700 ml of Momordica charantia seed oil was heated to approximately 50–65 °C for 40–60 min to remove remaining moisture. The catalyst used in this experiment was 4 g of sodium hydroxide, and the alcohol utilized was 200 ml of methanol. Both were combined and spun at room temperature for 30–45 min without heat. The mixer was connected to a reflux condenser, which allowed the methanol to be recovered. It was referred to as sodium methoxide, and it was a homogenous combination[27]. The sodium methoxide solution was combined with hot orange oil at 60–65ºC for 60 min. The mixed solution was continually spun at 600–650 rpm using a magnetic stirrer. Settle the solution obtained in a separate funnel. Two different layers of crude methyl ester and crude glycerol were detected after 24 h, with crude methyl ester ascending upward and crude glycerol falling below. Water washing was used to increase methyl ester purity. A known amount of warm distilled water was added to the resultant crude methyl ester and forcefully agitated in the separation funnel. Impurities and water sink to the bottom after 24 h, while methyl ester rises to the top. The above procedure was done thrice to increase the methyl ester concentration[28]. The resulting ester is also heated around 60 °C to eliminate any remaining water molecules. After the heating procedure, the solution produced was designated as Momordica charantia seed biodiesel (MCSO). In the present study, 20MCSO (80% diesel and 20% Momordica charantia) was employed as a biodiesel in a diesel engine with good results. The features of mineral diesel and 20MCSO trials were investigated in the laboratory under controlled circumstances. Table 2. compares the different physical and chemical characteristics of Momordica charantia to diesel.

CeO_2 is a versatile metal oxide nanoparticle capable of performing as a combustion enhancer in biodiesel due to its extraordinary physical and chemical properties. Physically, the CeO_2 nanoparticles are characterized by a large surface area about their volume since they possess excellent thermal stability, shown by their melting point, approximately 2400 °C. Chemically, CeO_2 consistently reduces and oxidizes between Ce^{3+} and Ce^{4+} states, thereby functioning as an oxygen buffer during combustion. This ability allows CeO_2 to supply additional oxygen molecules and enhance the complete oxidation of fuel, significantly reducing unburnt hydrocarbon (HC) and carbon monoxide (CO) emissions[17].

Reportedly, CeO_2 in the combustion process enhances flame propagation and raises thermal conductivity, thus ensuring rapid heat transfer and stable combustion temperatures. Reportedly, CeO_2 nanoparticles may increase brake thermal efficiency (BTE) by 10–12% and significantly reduce HC, CO, and smoke emissions by 44, 60, and

Nanoadditives	Nano Ratio	Biodiesel Name	BTE	SFC	CO	HC	NOx	Smoke	Ref.
Al2O3, TiO2	25 ppm, 50 ppm	Rubber seed oil biodiesel	↑ 5.2%	↓ 10.56%	↓ 44%	↓ 28%	↑ 21%	↓ 44%	18
CeO2, Al2O3	30 ppm each	Biodiesel	↑ 12%	-	↓ 60%	↓ 44%	↓ 30%	↓ 38%	19
TiO2	100 ppm, 200 ppm	Mahua biodiesel	-	-	↓ 9.3%	↓ 5.8%	↓ 6.6%	↓ 2.7%	20
GO	30, 60, 90 ppm	Ailanthus altissima biodiesel	-	↓ Significantly	↓ 7–20%	↓ 15–28%	↑ 5–10%	-	21
Al2O3	10, 20, 30 ppm	Jatropha biodiesel	↑ 7.8%	↓ 4.93%	↓ 11.24%	↓ 5.69%	↓ 9.39%	↓ 6.48%	22
CeO2	100 ppm	Tyre pyrolysis oil	↑ 2.85%	-	↓ 1.33%	↓ 3%	-	↓ 7.7%	23
CuO	100 ppm	Pongamia biodiesel	↑ 4.01%	↓ 1%	↓ 29%	-	↓ 9.8%	↓ 12.8%	24

Table 1. Literature on nano additive impact on biodiesel performance.

Property	Diesel	MCSO	ASTM Standards
Calorific Value (MJ/kg)	43.2	34.4	D 240
Kinematic Viscosity at 40 °C (CST)	3.90	3.48	D 445
Density (kg/m^3)	823.1	811.2	D 1298
Flash Point (°C)	56	161	D 93
Calculated cetane index	47	46	D 976
Oxygen Content (%)	0.04	11	D6751

Table 2. Properties of momordica charantia seed biodiesel.

Fig. 1. Experimental setup of Engine.

38%, respectively. Additionally, using CeO_2 nanoparticles provides a cure for some of the biodiesel's problems: high viscosity and ignition delay, permitting a better quality of atomization and combustion. In addition to enhancing biodiesel performance, this enables cleaner and more efficient engine operation, spotlighting the prominent role of CeO_2 as a performance and emission-reduction additive[14,23,29].

After preparation of Momordica charantia seed oil biodiesel using transesterification and purification, it was mixed in a 20:80 (biodiesel: diesel) volume ratio to create a 20MCSO blend with commercial diesel fuel. To improve this blend, 45 ppm of cerium oxide (CeO_2) nanoparticles was incorporated. The initial mixing of the nanoparticles into the biodiesel-diesel blend was done in a magnetic stirrer for about 20 min for the preliminary dispersion of CeO_2 nanoparticles. As a final step, the mixture was ultrasonicated at 40 kHz and 400 W for 45 min to ensure uniform distribution and stability. This further facilitated nanoparticle dispersion, breaking agglomerates and allowing for a stable nano-enhanced fuel blend. Once the blend was completed, an assessment of the stability of this fuel against CeO_2 nanoparticle agglomeration was conducted using a UV-Vis spectrophotometer. This confirmed consistent and long-term dispersion of CeO_2 nanoparticles in the fuel matrix.

Experimental details

An eddy current dynamometer-linked four-stroke single-cylinder diesel engine is a regularly utilized engine for small, medium, and large commercial applications. Because of its high compression ratio, it can withstand high pressure. To evaluate the performance and emission studies of the chosen compression ignition engine under various running situations, a laboratory setup was built to test the engine using various fuel types. The components of the experimental setup are discussed in further detail in the following sections and shown in Fig. 1.

The engine used for the investigation was a water-cooled four-stroke DI diesel engine. It had a bore of 87.5 mm and 110 mm. The engine generates power at a constant speed of 1500 rpm is about 5.2 kW, with a compression ratio of 16.5:1. Injection pressure at 210 bar, and injection duration was 23 °bTDC. Thermal performance measures, mean effective pressure, specific fuel consumption, brake thermal efficiency, and exhaust gas temperature were obtained using performance analysis software for the lab view engine. The exhaust gases also identified HC, CO, NOx, and smoke.

The coating material employed in this study is partly stabilized zirconia. PSZ was a low-conductivity ceramic material with a low coefficient of thermal expansion. As a result, it is more resistant to corrosion than other metals. In addition, the PSZ coating increased the combustion temperature, which improved the combustion characteristics of the biodiesel and reduced CO and HC emissions. Before coating, all components received a 150 µm thick PSZ bond coat to enhance the bonding of the coating material. However, when applied to the engine components, the coating material was limited to a thickness of 300 µm. When the thickness of the cylinder wall increases, the amount of air that enters the cylinder decreases, decreasing the engine's volumetric efficiency[29]. Figure 2. illustrates the SEM images of the thermal barrier coating on the engine piston head.

This image is a micrograph of cerium oxide (CeO_2) that appears under a microscope with a magnification of 1.00 KX and a scale bar of 10 µm. The morphology observed from the micrograph suggests that CeO_2 nanoparticles exhibit a heterogeneous granular character. These characteristics visible on the images, like cracks or pores, may be ascribed to particle agglomeration or just how they were prepared. Such structural features are highly critical to its application in combustion catalysis. CeO_2 nanoparticles are powerful fuel combustion improvement agents, as they catalyze oxidation in the biodiesel by reducing emissions and increasing thermal efficiency as additives. Further analysis indicates that CeO_2 possesses great surface area, thus further contributing to effective catalytic activity, making it a suitable candidate for better performance of biodiesel in engines[23,14,40]. This study did not include detailed surface analyses like Scanning Electron Microscopy (SEM), Energy Dispersive Spectroscopy (EDS), or evaluations of porosity and hardness for the PSZ coating. However, we kept the coating thickness at 300 µm and the bond coat at 150 µm. This choice follows previous research to ensure the thermal barrier works well. This research aimed to evaluate how well a PSZ-coated engine performs with Momordica biodiesel blends. It also focused on creating machine learning models to predict performance and emissions. The coating was applied evenly with atmospheric plasma spraying. We used standard pre-treatment to improve adhesion and ensure consistency. Although UV-Vis spectroscopy or Zeta potential analysis was not performed to validate nanoparticle dispersion, the nano-blend fuels were prepared through controlled stirring and ultrasonication to maintain homogeneity prior to each test cycle. These measures ensured consistent experimental conditions aligned with the objective of evaluating the system's thermal response under practical engine operating scenarios.

Experimental uncertainty analysis

Experimental uncertainty analysis is essential for understanding the variability in the measurements obtained during experimentation. This variability can arise due to factors such as environmental conditions, equipment used, instrument calibration, and observation precision. The propagation of error method, as outlined by J.P. Holman[39], was used to quantify the total uncertainty. The total uncertainty was calculated using the root-sum-square method, which involves summing the squares of individual uncertainties.

The total uncertainty is computed as (1):

$$Total\, Uncertainty = \sqrt{[TFC^2 + Bp^2 + BFSC^2 + BTE^2 + CO^2 + HC^2 + NO^2 + Smoke^2 + {T_{ex}}^2 + Pressure\, drop^2}$$

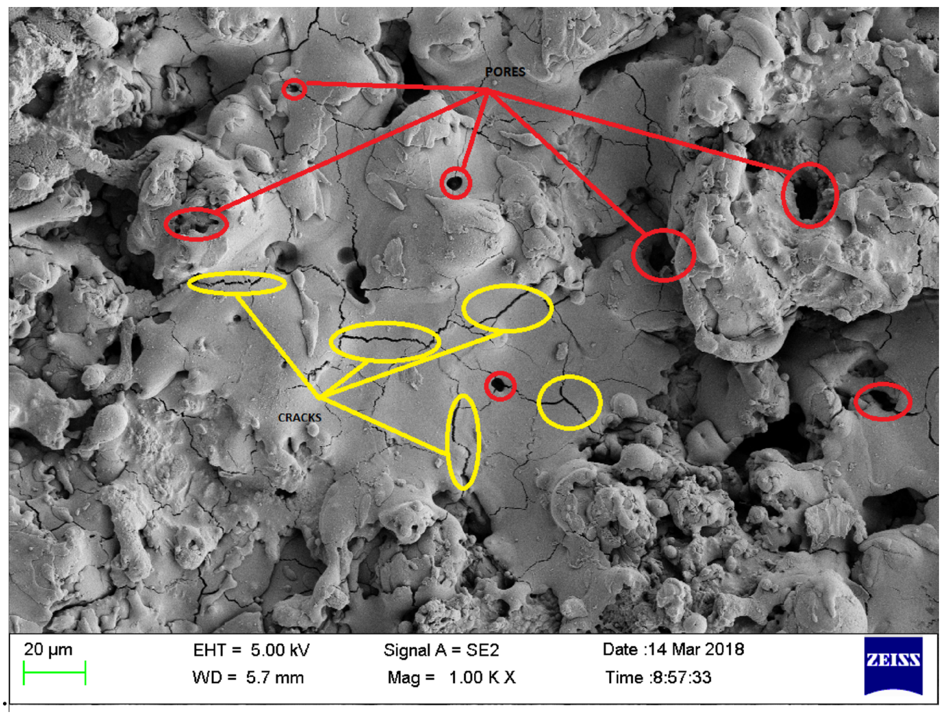

Fig. 2. SEM image of thermal barrier coating.

$$Total\ Uncertainty = \sqrt{(1^2 + 0.2^2 + 1^2 + 1^2 + 0.2^2 + 0.1^2 + 0.2^2 + 1^2 + 0.15^2 + 1^2)} = \pm 2.27\% \quad (1)$$

This total uncertainty value of ± 2.27% represents the aggregate uncertainty in the entire measurement process.

Results and discussion
Brake thermal efficiency
Figure 3 shows that Effect of MCSO's Brake Thermal Efficiency on Coated EngineThe brake thermal efficiency (BTE) measures how efficiently an engine harnesses fuel energy for practical work. The performance of the coated CI engine, powered by biodiesel blends of Momordica seed oil, is improved by various nanoparticle additives. Diesel invariably has the highest BTE, 28% at full load (100%). Amongst the biodiesel blends, B10 with 45 ppm nanoadditives shows the best performance by way of thermal efficiency during most loads. High surface area and catalytic properties of nanoparticles assist in increasing flame propagation speed and improving combustion efficiency for better fuel utilization. At lower loads, the inherent thermal properties of biodiesel help maintain the optimal cylinder temperature and aid in combustion with low-calorific-value fuels. Nanoadditives, like CeO_2, reduce ignition delays and promote complete combustion by increasing the amount of oxygen and improving heat transfer characteristics. BTE showed a marginal decrease with the increasing blend ratio for biodiesel blends, with maximum efficiencies of 26%, 25%, and 24% for B10, B20, and B30, respectively, under full load. The effective performance of the nanoparticles considerably offsets high-viscosity fuel coupled with slow

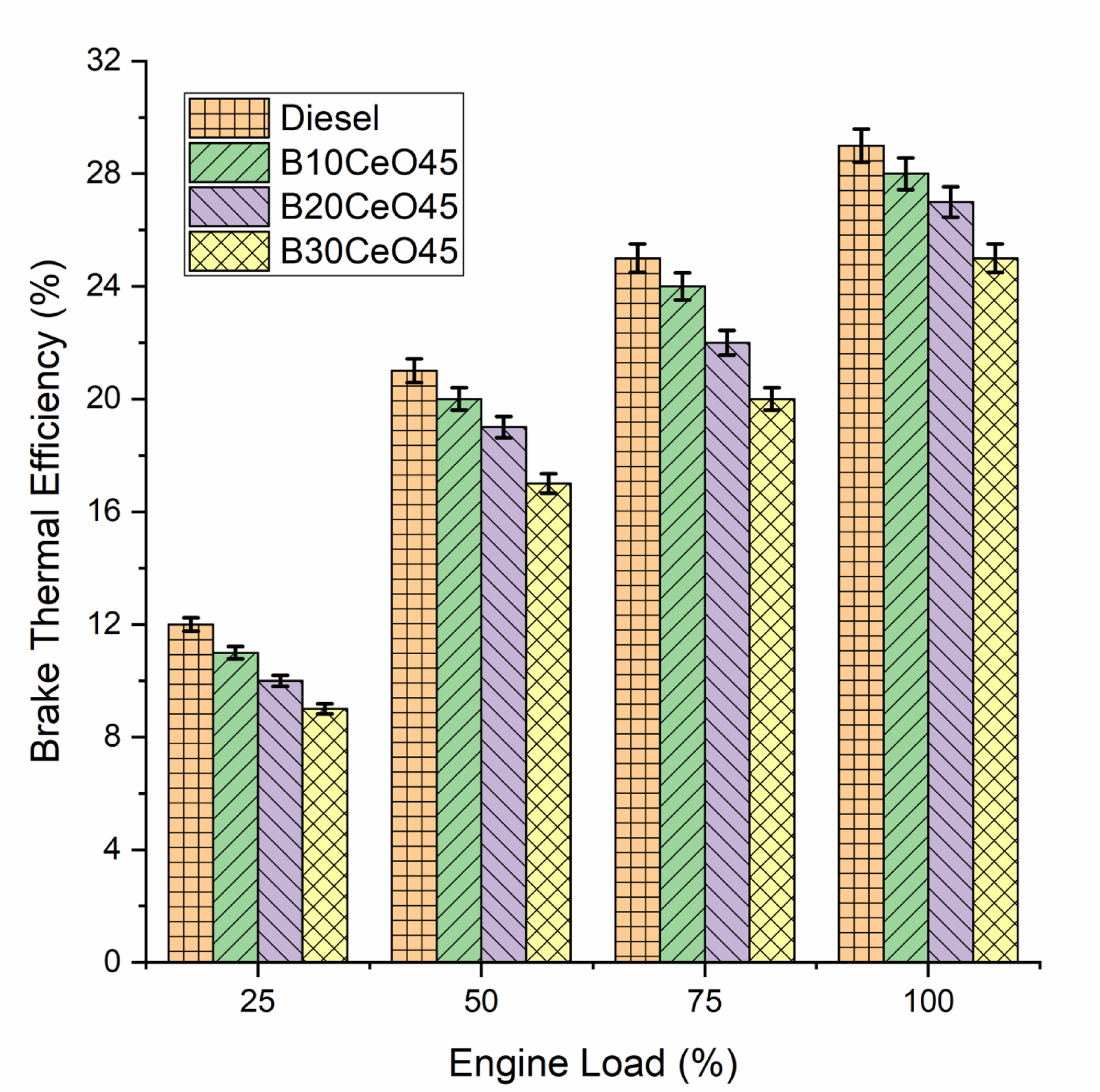

Fig. 3. Effect of MCSO's Brake Thermal Efficiency on Coated Engine.

ignition in biodiesel. Improved flame length and adjustment of the air-fuel ratio of the coated CI engine assure higher energy conversion efficiency. This indicates the importance of combustion strategies and nanoadditives for achieving higher BTE than the ordinary use of biodiesel[3,16].

Specific fuel consumption

Figure 4 shows that Effect of MCSO's Specific Fuel Consumption on Coated Engine Specific fuel consumption (SFC) is a fuel economy indicator-quantifier: fuel needed to produce a unit of energy. In a PSZ-coated CI engine fueled with Momordica seed oil biodiesel, the specific fuel consumption (SFC) is significantly reduced by incorporating nanoadditives and advanced combustion strategies. At 75% load, the B20 blend with 45 ppm nanoadditives achieved the lowest SFC of 0.26 kg/kWh, compared to 0.47 kg/kWh for conventional diesel under similar conditions. Metal oxide Nano additives promote secondary atomization and a better fuel-air mixture, leading to more complete combustion and decreased unburnt fuel. Nano additives additionally increase the thermal conductivity of fuels, making them more reactive fuels rapidly vaporize into the engine, thus stabilizing the combustion and reducing the wastage of fuels. More benefits arise from combustion strategies that use coated cylinder surfaces to maintain higher temperatures, effectively controlling flame propagation. For instance, 0.33 kg/kWh for B10 and 0.29 kg/kWh for B30 provide some equity evidence to diesel by cutting down fuel consumption significantly. Findings emphasize the role of nanoparticles and combustion-enhancing techniques in combating the high consumption of biodiesel due to a lesser calorific value and higher viscosity[11].

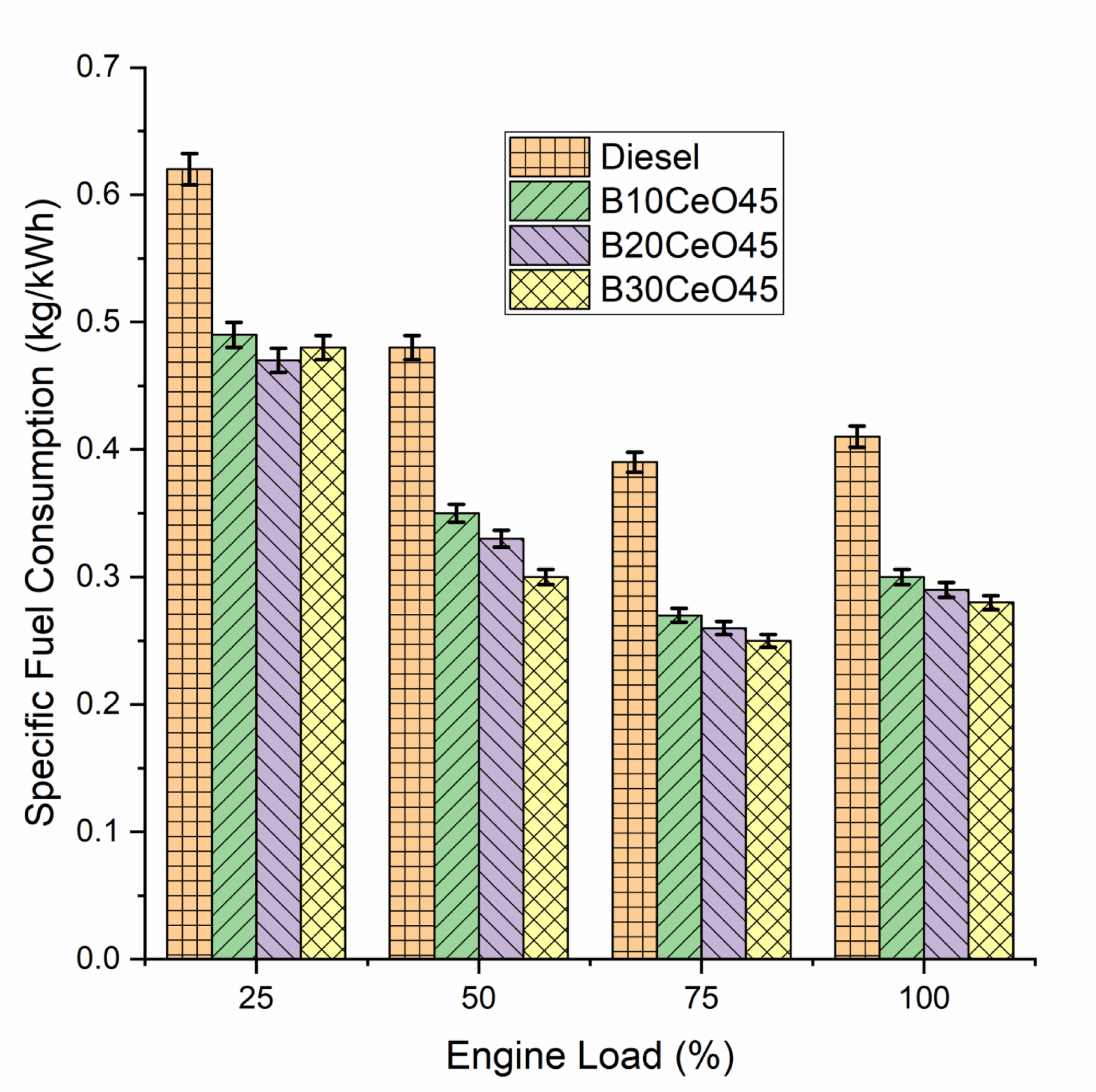

Fig. 4. Effect of MCSO's Specific Fuel Consumption on Coated Engine.

Carbon monoxide emission

Carbon monoxide emissions in compression ignition engines are caused mainly by insufficient oxygen or low temperatures within the engine cylinders, resulting in incomplete combustion. The effectiveness of reducing CO emissions is demonstrated by the analysis of an experimental nanocoated CI engine running on Momordica seed oil biodiesel mixtures with the aid of nanoadditives. Among the different fuels tested at full engine load, nano additives inclusion in B10 with 45 ppm gave the lowest overall CO emission, 0.02%, due to better oxygen availability of the system, enabling more effective combustion. Nanoparticles CeO_2 can function as oxygen carriers and significantly reduce unburnt hydrocarbons and carbon monoxide levels by speeding their oxidation process. The elevated surface area-to-volume ratio enhances nanoparticles' ability to mix more readily with air fuel, thereby converting energy even more efficiently under higher load conditions. Although diesel gave the highest CO emissions overall loads, biodiesel blends such as B20 and B30 had similarly low emissions at 0.021% and 0.020%, respectively, at 75% load. The coated surface in the cylinder aided in keeping the temperature of combustion high and helped further reduce CO. These results confirm the benefit of using biodiesel modified with nanoparticles upon delivering a cleaner engine operation and CO emission under different load conditions[30,31]. Figure 5. Shows that Effect of MCSO's Carbon Monoxide on Coated Engine.

Carbon dioxide emission

Figure 6 shows that Effect of MCSO's Carbon Dioxide on Coated Engine. Carbon dioxide (CO_2) emissions experienced in engines are attributable to complete combustion. The Momordica seed oil biodiesel blends-

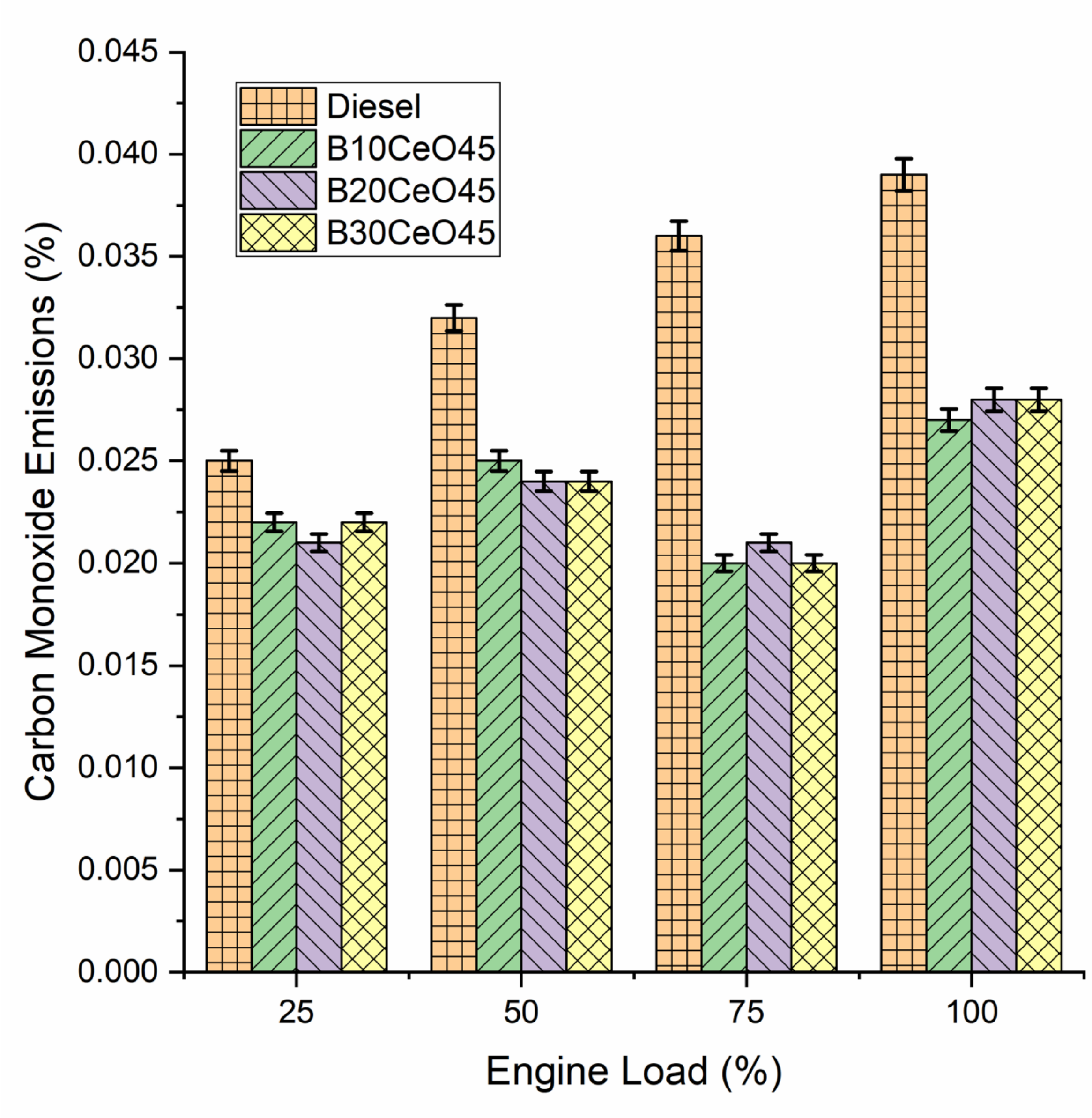

Fig. 5. Effect of MCSO's Carbon Monoxide on Coated Engine.

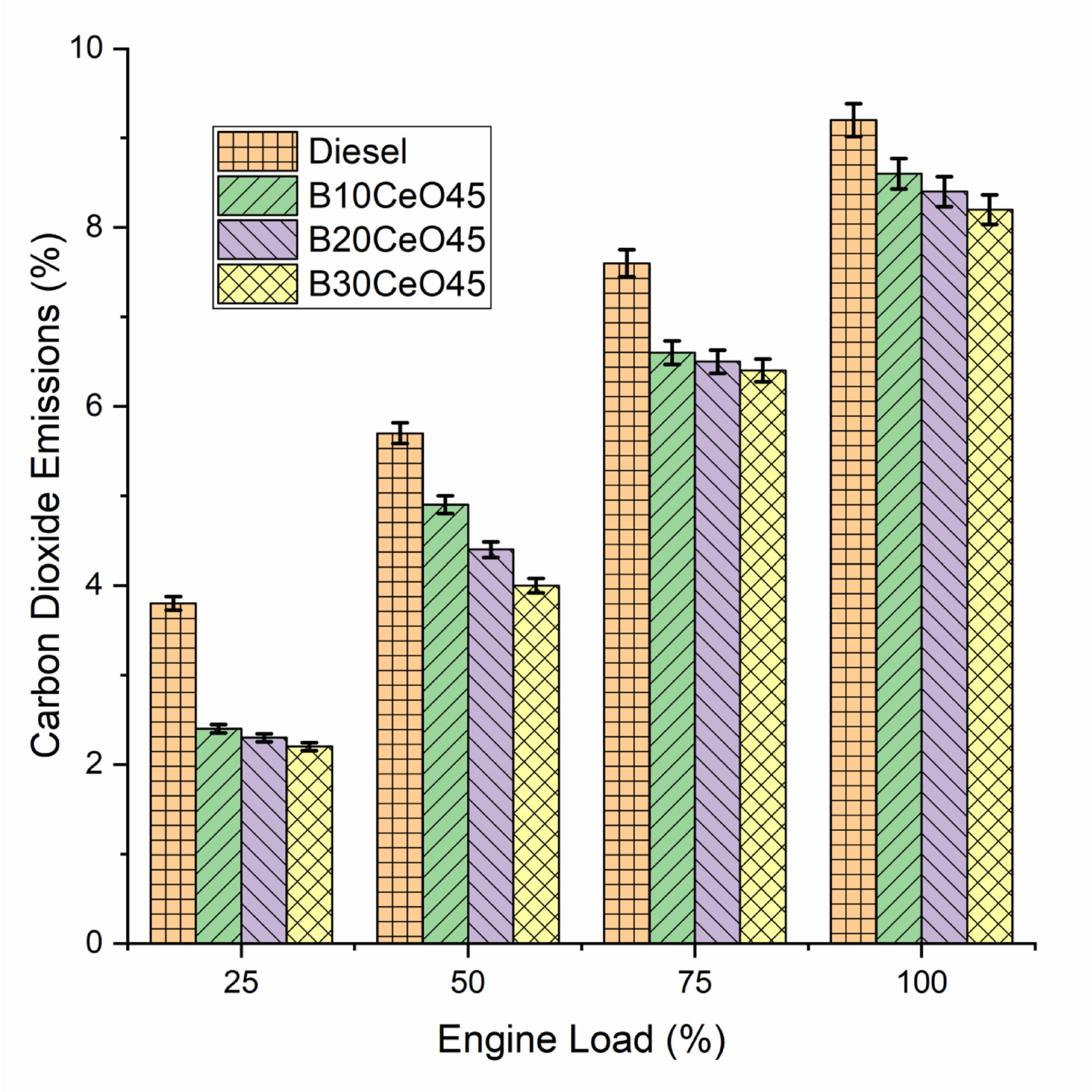

Fig. 6. Effect of MCSO's Carbon Dioxide on Coated Engine.

coated CI engine exhibited lower CO_2 emissions than diesel in all load conditions. The lowest CO_2 emission was observed at 25% load using B30 biodiesel and amounted to 2.2%, denoting the possible influence of combustion strategies and nanoparticle additives in controlling greenhouse gas emissions. Nanoparticles enhance combustion efficiency by increasing the ventilation of flame propagation and improving heat transfer. This results in better oxidation, reducing the residual hydrocarbons and lowering CO_2 emissions. Even at full load conditions with more significant CO_2 emissions, biodiesel blends provided a consistent advantage over diesel in controlling emission levels owing to its renewable and rich-oxygen nature that favors cleaner combustion in the engine. The coated surfaces keep combustion temperature relatively constant, allowing complete combustion due to the absence of instant bursts of CO_2 emission. The synergistic effect of nanoparticles and coatings on the engine surface permits a reasonable path toward lower emissions with relatively maintained performance[10,11].

Hydrocarbon emission

Figure 7 shows that Effect of MCSO's Hydrocarbon on Coated Engine. The hydrocarbon (HC) emissions arise from poor combustion in internal combustion engines; the study reviews the performance of a coated CI engine fuelled with Momordica seed oil biodiesel blends, showing a significant reduction in HC emissions with the aid of nanoparticle additives along with optimized combustion strategies. Of all the fuels tested, B30 biodiesel produced the lowest HC emission of 31 ppm at 25% engine load, followed by diesel and the rest of the biodiesel blends. Likewise, B10 and B20 blends have recorded HC emissions of 33 ppm and 31 ppm, respectively, compared to 36 ppm for diesel. Adding nanoadditives such as titanium oxide (TiO_2) and aluminum oxide

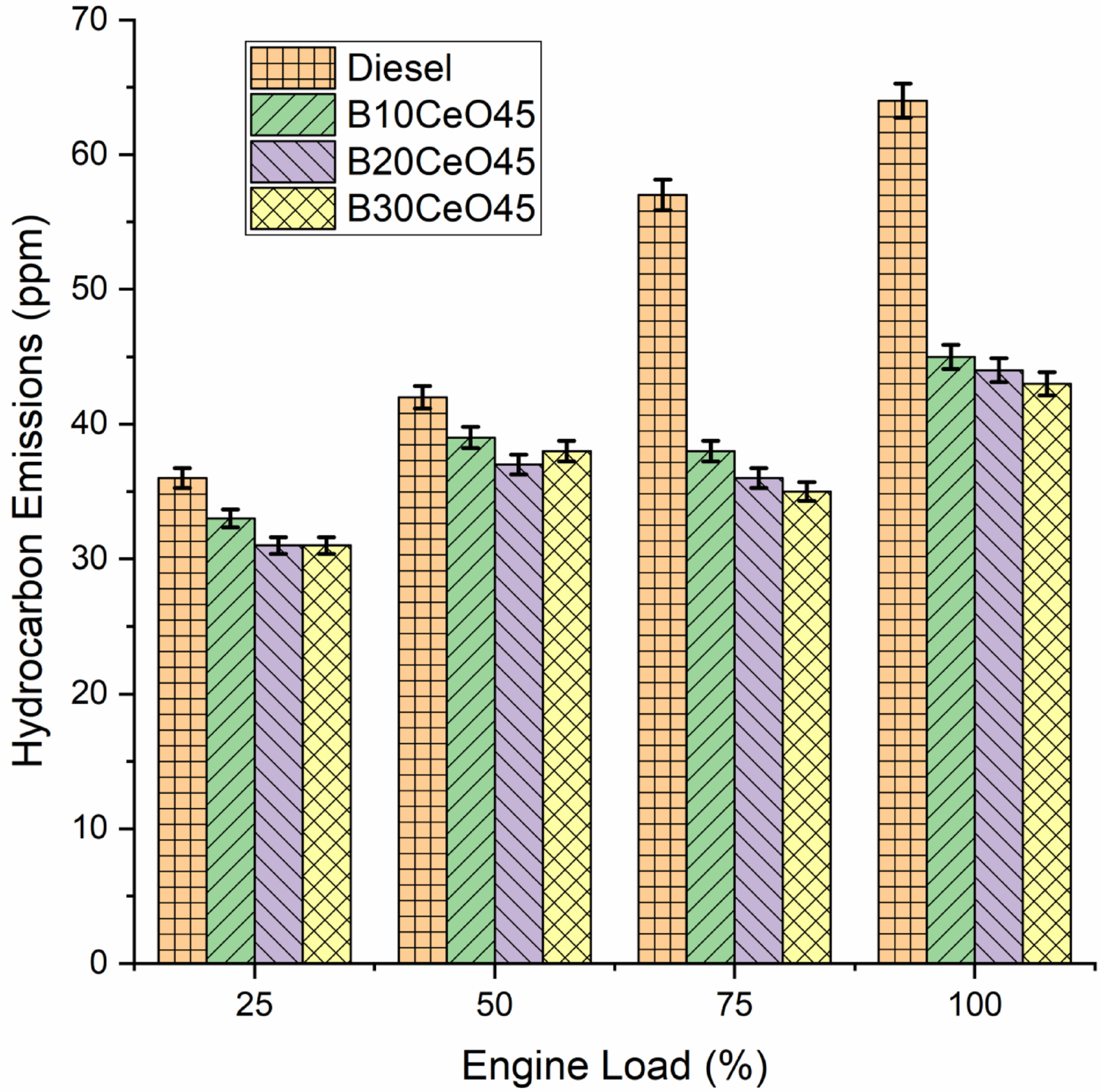

Fig. 7. Effect of MCSO's Hydrocarbon on Coated Engine.

(Al_2O_3) improves biodiesel's ignition quality and flame propagation characteristics[16]. It promotes more complete combustion while reducing unburnt hydrocarbon emissions. The nanoparticles act as catalysts for secondary atomization and as a distribution fortifier, resulting in improved fuel-air mixing, which reduces hydrocarbon formation. Coated cylinder surfaces ensure optimum combustion temperatures, inhibiting quenching and allowing complete hydrocarbon oxidation. In their report, the two professors have substantiated the synergistic action of biodiesel, nanoadditives, and advanced combustion systems in minimizing HC emissions, thereby allowing cleaner engine[17,31].

Oxides of nitrogen emission

Figure 8 shows that Effect of MCSO's Oxides of Nitrogen on Coated Engine. Combustion temperature and the quantity of oxygen available for complete combustion most influence NOx emissions from diesel engines. The coated CI engine runs on momordica seed oil biodiesel blends; it shows a marked drop in NOx emissions, especially under light engine loads. NOx emissions with B30 biodiesel at 25 loadings were recorded at the lowest level of 228 ppm, followed by B20 at 230 ppm and B10 at 235 ppm emissions compared to 250 ppm of diesel. Nanoadditives like cerium oxide (CeO_2) improve flame temperature control and the oxidation reaction during combustion. Improvement in fuel-air mixing and thermal conductivity helps stabilize the responses with controlled kinetics, limiting the excessive NOx formation. The coated surfaces of the cylinder stabilize combustion, allowing energy conversion without excessively increasing the peak temperatures. This balance effectively minimizes NOx emissions while maintaining performance. These findings provide compelling

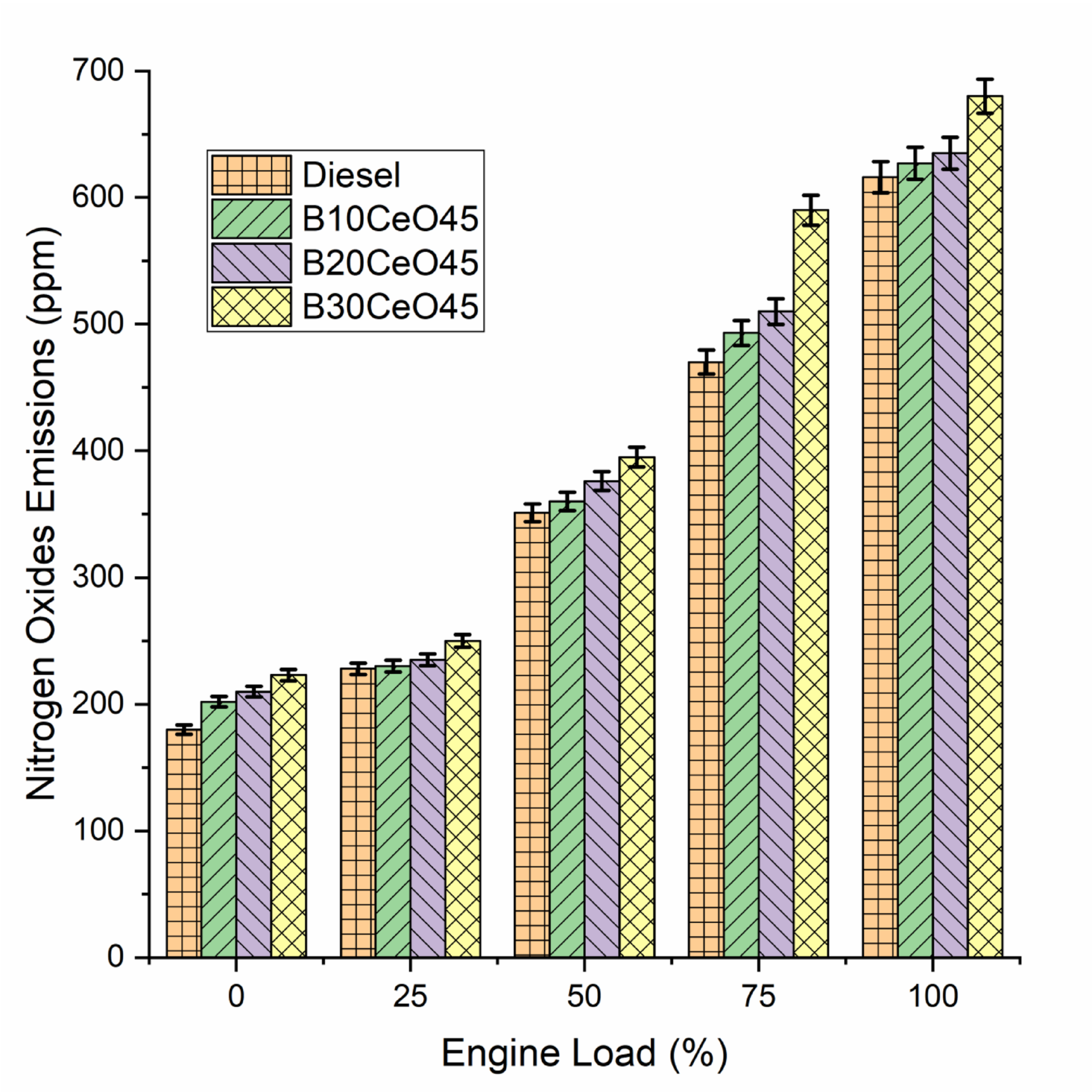

Fig. 8. Effect of MCSO's Oxides of Nitrogen on Coated Engine.

evidence for nanoparticle-enhanced biodiesel blends and engine coatings to mitigate the environmental issues of NOx emissions[8,13].

Smoke emission

Figure 9 shows that Effect of MCSO's Smoke on Coated EngineSmoke emissions from internal combustion engines result from incomplete combustion and soot particle presence. Compared to diesel, analyzing a coated CI engine powered by Momordica seed-oil biodiesel blends has considerably improved smoke emissions. The lowest smoke emission of 11 HSU was observed with B10 biodiesel at 25% engine load, while slightly higher values of 12 HSU and 14 HSU were observed for B20 and B30, respectively. In contrast, diesel recorded values of ISU at low loads, benefiting from relatively deep fuel flow and delayed combustion through the traditional fuel–combustion concentrations. Adding nanoadditives metal oxides in biodiesel blends undeniably enhanced combustion efficiency while reducing soot formation. This occurs due to increased flame propagation speed and thermal conductivity promoted by better fuel atomization, enabling carbonaceous compounds' post-combustion oxidation. Further, coated surfaces of the cylinder maintain combustion temperatures with no formation of particulate matter and hence a lower soot release into the environment. The oxygen-rich nature of biodiesel enhances the complete burning process, thus further reducing soot and smoke through different load profiles. The results illustrate a very inspiring synergistic relationship between initially nano-particle-enhanced biodiesel and the continued advancement of engine coatings in reducing smoke emissions, giving biodiesel an edge over conventional diesel fuels as a clean and greener alternative[14].

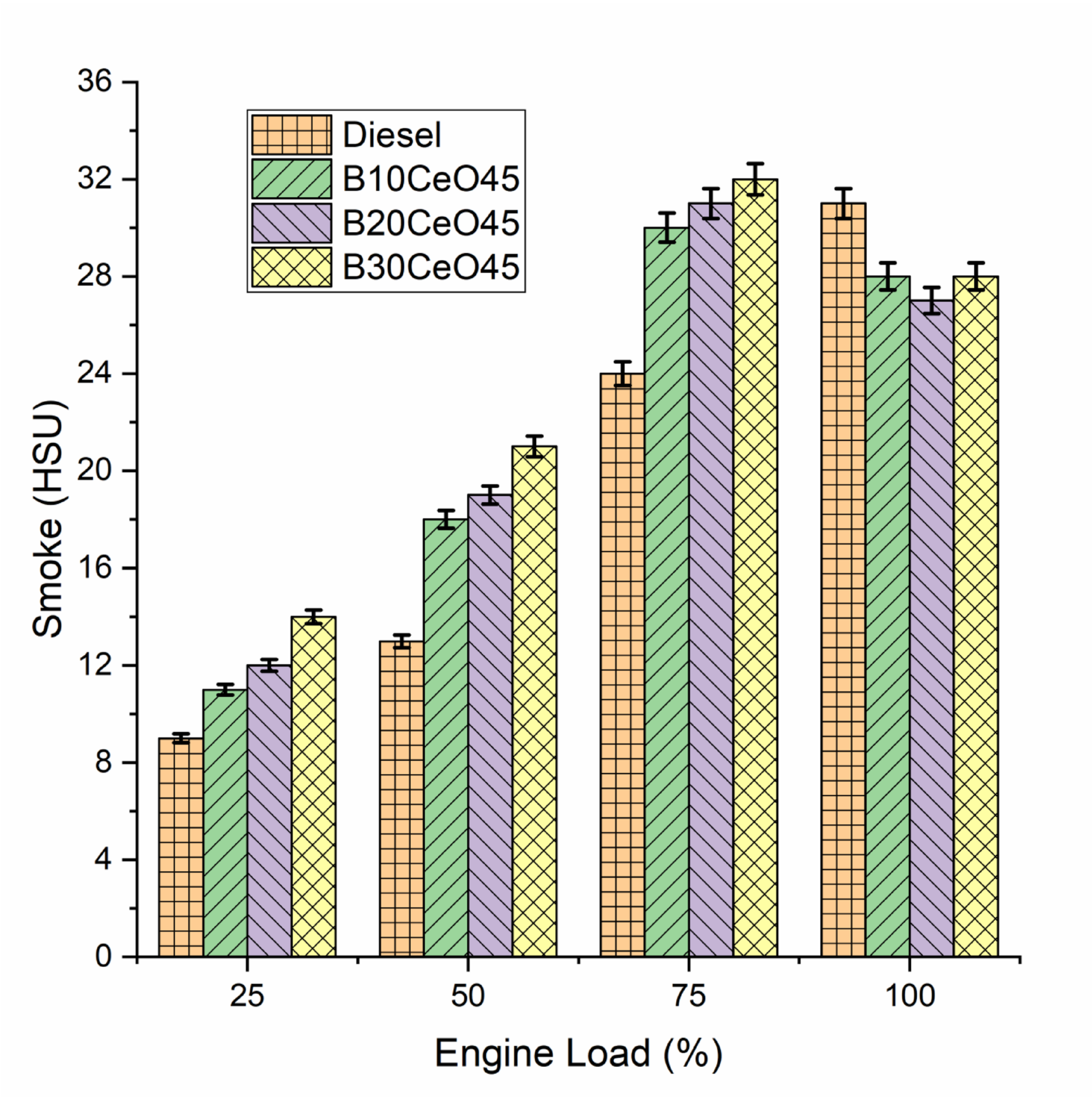

Fig. 9. Effect of MCSO's Smoke on Coated Engine.

Evaluation of machine learning algorithms for thermal performance prediction

The primary goal of the machine learning (ML) modeling in this study is to establish predictive relationships between the key operating parameters of biodiesel-fueled engines and their performance and emission characteristics. By leveraging ML algorithms, the study aims to uncover complex nonlinear patterns that influence critical metrics such as brake thermal efficiency, combustion characteristics, and exhaust emissions. This approach not only enhances predictive accuracy but also facilitates the identification of optimal conditions for maximizing biodiesel performance and minimizing environmental impacts. The ML models are designed to complement experimental findings, offering a robust framework for real-world implementation and decision-making in biodiesel optimization.

Machine learning project life cycle

The Machine Learning (ML) project life cycle involves several key stages, ensuring a structured approach to problem-solving. It begins with problem definition, where objectives and constraints are identified. Next is data collection and preprocessing, including gathering, cleaning, and transforming raw data for model input. The exploratory data analysis (EDA) phase follows, where patterns, correlations, and distributions are analyzed. Feature engineering and selection refine relevant variables, improving model performance. The model selection and training stage involves choosing appropriate algorithms and optimizing hyperparameters. Afterward, model evaluation using performance metrics such as accuracy, precision, recall, or RMSE ensures reliability. The deployment phase integrates the model into real-world applications, followed by monitoring and maintenance, where performance is tracked and models are retrained as needed.

Modeling

The modeling approach in this study involves the development and validation of machine learning models to predict engine performance and emission outcomes based on experimental data. The methodology begins with preprocessing the dataset to handle missing values, normalize input parameters, and remove outliers, ensuring data quality and consistency. Feature selection techniques, such as recursive feature elimination or correlation analysis, are applied to identify the most influential parameters affecting engine performance. Subsequently, ML algorithms like Random Forest, Support Vector Regression (SVR), and Neural Networks are employed to construct predictive models.

Hyperparameter tuning is performed to enhance model performance by optimizing key parameters specific to the machine learning algorithms applied in this study. For instance, in the Random Forest model used to predict engine performance and emissions, the number of trees (n_estimators) and the maximum depth of the trees (max_depth) are optimized. In the Support Vector Regression (SVR) model, the kernel type, regularization parameter (C), and epsilon (ε) are fine-tuned to capture nonlinear relationships effectively. For the Neural Network models applied to this study, the optimization focuses on the number of hidden layers, the number of neurons per layer, learning rate, and activation functions to achieve robust predictions.

These parameters were selected to address the complexity of interactions between experimental variables, such as the type and concentration of metal oxide nanoparticles, coating properties of zirconia, and the biodiesel blend ratios. A combination of grid search and Bayesian optimization techniques is employed to systematically identify the optimal values, ensuring that the models capture the nuanced relationships affecting engine performance and emissions with high precision.

Data collection process

We collected data using a single-cylinder, four-stroke, water-cooled CI engine test rig. This setup was made to assess the performance, combustion, and emissions of biodiesel blends with a 45 PPM additive. The engine operated at a constant speed of 1500 RPM and a fixed injection timing of 23° before top dead center (BTDC). We tested four fuel types: three biodiesel blends (B10 + 45 PPM, B20 + 45 PPM, B30 + 45 PPM) and neat diesel. These were evaluated at four compression ratios (CR: 14.5, 15.5, 16.5, and 17.5) and four engine load levels (25%, 50%, 75%, and 100%). This created a total of 48 structured test conditions.

We measured performance parameters: Brake Power (BP), Brake Thermal Efficiency (BTE), and Specific Fuel Consumption (SFC) using an Eddy Current Dynamometer. This device had digital tools for torque and speed measurement. We measured peak cylinder pressure and combustion traits. These include Ignition Delay (ID), Heat Release Rate (HRR), and Indicated Mean Effective Pressure (IMEP). A piezoelectric pressure transducer worked with a high-speed data acquisition (DAQ) system. This setup was synced with crank angle measurement.

We recorded emission parameters like Carbon Monoxide (CO), Hydrocarbons (HC), Nitrogen Oxides (NOx), and smoke opacity. We used a calibrated AVL 444 five-gas analyzer and a smoke meter for these measurements. We repeated each test condition three times. This ensured repeatability. We then used the average of the three runs for analysis. This helped minimize random error and improve data reliability.

Prior to modeling, the dataset was thoroughly validated for completeness and consistency. The experiments created a balanced dataset for machine learning. It included enough variety in fuel types, CR, and load conditions. Table 3 shows the experimental setup, operating parameters, and instruments used. Table 4 shows peak pressure, brake thermal efficiency, specific fuel consumption, and emissions across various engine settings.

We improved the technical validation and transparency of the machine learning framework in this study. All experimental datasets for model training and validation are now detailed in the updated Table 4. This table shows various operational scenarios. It covers different fuel blends, engine loads, and compression ratios. Figures and tables in the manuscript are clearer and more accurate now. They have uniform scaling, correct units, and easy-to-understand legends. This helps with interpretation.

Parameter Type	Details
Experimental Setup	Fixed RPM: 1500, Injection Timing: 23° before TDC
Fuel Blends	B10 + 45 PPM, B20 + 45 PPM, B30 + 45 PPM, Diesel
Engine Parameters	Compression Ratio (CR): 14.5–17.5, Load (%): 25–100
Performance Metrics	Indicated Power (IP), Indicated Mean Effective Pressure (IMEP), Peak Pressure(bar), Brake Power (BP), Brake Thermal Efficiency (BTE), Specific Fuel Consumption (SFC)
Combustion Parameters	Ignition Delay (ID), Cylinder Pressure, Heat Release Rate
Emission Metrics	CO (%), HC (PPM), CO2 (%), O2 (%), NOx (PPM), Smoke (mg/m³)
Instrumentation	- Eddy Current Dynamometer (for performance parameters)
	- Multi-Gas Analyzer (for emission measurements)
	- Pressure Transducers and DAQ System (for combustion metrics)
Repetitions	Each experiment was repeated three times to ensure reproducibility

Table 3. Summary of dataset and experimental parameters.

Exp. No.	Blend	CR	Load (%)	Peak Pressure (Bar)	BTE (%)	SFC (kg/kWh)	CO (%)	HC (PPM)	NOx (PPM)	Smoke (mg/m³)
1	B10 + 45 PPM	14.5	25	150	11	0.58	0.023	37	270	13
2	B10 + 45 PPM	14.5	50	210	16	0.42	0.022	35	310	16
3	B10 + 45 PPM	14.5	75	300	21	0.34	0.024	38	420	21
4	B10 + 45 PPM	14.5	100	400	26	0.29	0.025	41	590	27
5	B10 + 45 PPM	15.5	25	170	13	0.53	0.021	36	280	14
6	B10 + 45 PPM	15.5	50	250	20	0.38	0.024	42	460	22
7	B10 + 45 PPM	15.5	75	320	23	0.31	0.026	39	500	30
8	B10 + 45 PPM	15.5	100	420	27	0.28	0.027	44	620	38
9	B20 + 45 PPM	14.5	25	160	10	0.60	0.022	35	280	14
10	B20 + 45 PPM	14.5	50	250	17	0.44	0.021	33	340	17
11	B20 + 45 PPM	14.5	75	310	21	0.37	0.023	36	460	24
12	B20 + 45 PPM	14.5	100	390	25	0.32	0.025	40	580	32
13	B20 + 45 PPM	15.5	25	180	12	0.55	0.020	34	300	15
14	B20 + 45 PPM	15.5	50	260	19	0.40	0.022	38	470	23
15	B20 + 45 PPM	15.5	75	340	23	0.33	0.024	41	530	31
16	B20 + 45 PPM	15.5	100	430	28	0.30	0.026	43	640	40
17	B30 + 45 PPM	14.5	25	165	9	0.62	0.023	38	270	13
18	B30 + 45 PPM	14.5	50	230	15	0.45	0.022	36	330	18
19	B30 + 45 PPM	14.5	75	310	19	0.38	0.024	39	450	25
20	B30 + 45 PPM	14.5	100	400	24	0.33	0.026	42	590	34

Table 4. Obtained experimental dataset.

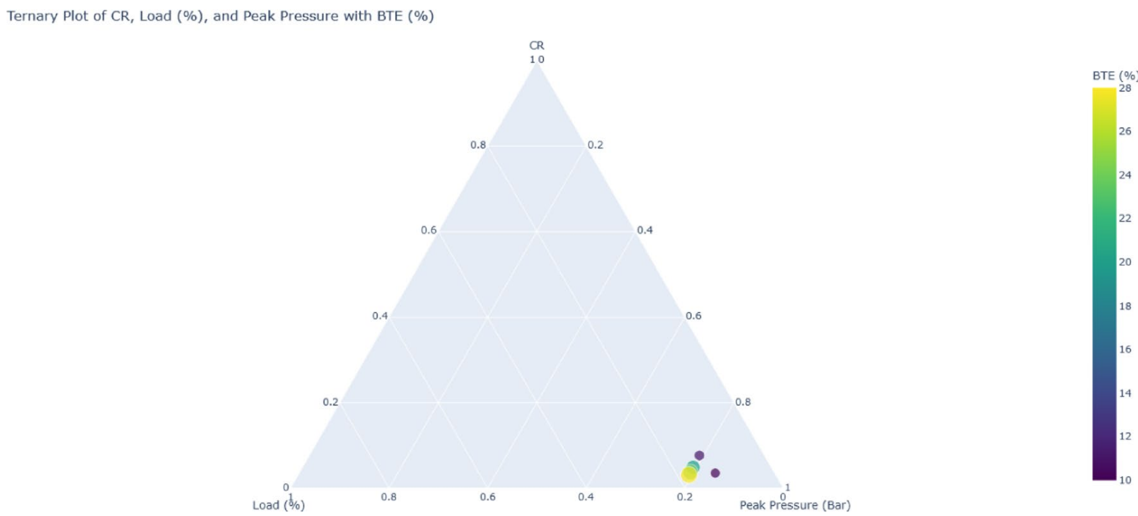

Fig. 10. Ternary plot for data distribution.

In the machine learning section, a more rigorous statistical evaluation has been introduced. We validated the model's performance with a 10-fold cross-validation approach. This method splits the dataset into several training and testing sets. It helps ensure generalizability and lowers the risk of overfitting. We added residual plots and error histograms for important output parameters. These include Brake Thermal Efficiency (BTE), Specific Fuel Consumption (SFC), and CO and NOx emissions. This helps us see how well the model predicts and spot any systematic biases. Here are the feature importance rankings from methods like Random Forest and Gradient Boosting Regression. These rankings show how engine parameters affect predicted outcomes. These additions make the machine learning analysis stronger. They also provide better insight into the physics of the biodiesel engine system. This improves the study's overall impact and reliability.

Data visualization and Pre-processing

To ensure a comprehensive understanding of the experimental data, we incorporated various visualization and statistical techniques. Ternary plots, shown in Fig. 10, were used to visually represent the relationships among critical input parameters such as Compression Ratio (CR), Load (%), and Peak Pressure, with Brake Thermal Efficiency (BTE) as the target metric. These plots provided a clear depiction of how variations in these engine parameters and biodiesel blend compositions (B10 +45 PPM and B20 +45 PPM) influenced thermal performance. The ternary visualization highlighted trends in engine performance metrics, aiding in understanding the interplay among the factors.

In addition to visual exploration, Pearson correlation analysis was performed shown in Fig. 11 to evaluate the relationships between input parameters (e.g., CR, Load, Peak Pressure) and target variables (e.g., BTE, Specific Fuel Consumption, and emissions). The correlation matrix revealed the degree of linear correlation, identifying key parameters with significant influence on target outcomes. Strongly correlated variables were noted to potentially address multicollinearity during model development. The results of the correlation analysis were visualized as a heatmap, providing a straightforward interpretation of variable interrelationships. For machine learning model development, the dataset was partitioned into training and testing subsets using a 70%−30% split. This ensured robust evaluation of the model's generalization capability by assessing its performance on an independent test set. Pre-processing steps included normalization of input features to standardize scales, encoding of categorical variables (e.g., fuel blends), and handling of outliers and missing data. These steps ensured that the dataset was clean, consistent, and ready for predictive modeling.

Data splitting, normalization, and hyperparameter optimization

For this study, the dataset was split into training and testing sets using a 70:30 ratio, ensuring that 70% of the data was used for training the models, and the remaining 30% was reserved for model testing. This ratio was selected to provide an adequate representation of both training and testing data, promoting reliable model evaluation.

To further improve the performance and stability of the models, normalization techniques were applied. Specifically, Min-Max Scaling (or Standardization, depending on the model and data requirements) was utilized to rescale the features to a standard range, ensuring that the models could process the data more effectively.

In terms of model optimization, we carried out a systematic hyperparameter tuning process. This involved using grid search and random search methodologies to explore the search space for key hyperparameters for each model. The grid search was applied to the Decision Tree and Random Forest models, optimizing parameters such as max_depth and min_samples_split (for Decision Tree) and n_estimators, max_features, and max_depth (for Random Forest). The Gradient Boosting Regressor was optimized using random search, targeting key hyperparameters like learning_rate, n_estimators, and max_depth.

The optimal hyperparameter configurations were selected based on cross-validation performance using the Mean Squared Error (MSE) as the evaluation metric. This approach was critical to ensuring that the models were fine-tuned for predictive accuracy while avoiding overfitting.

Results and discussion of ML analysis

In this study, we investigated the efficacy of various machine learning (ML) algorithms for predicting thermal performance metrics using input parameters such as Fuel, CR, Load, and Peak pressure. Three ML algorithms were applied: Multiple Linear Regression (MLR), Gradient Boosting Regression (GBR), and Random Forest Regression (RF). Performance metrics, including R2 score, Mean Absolute Error (MAE), and Mean Squared Error (MSE), were utilized to assess the accuracy of the predictions. ML algorithms are crucial in understanding

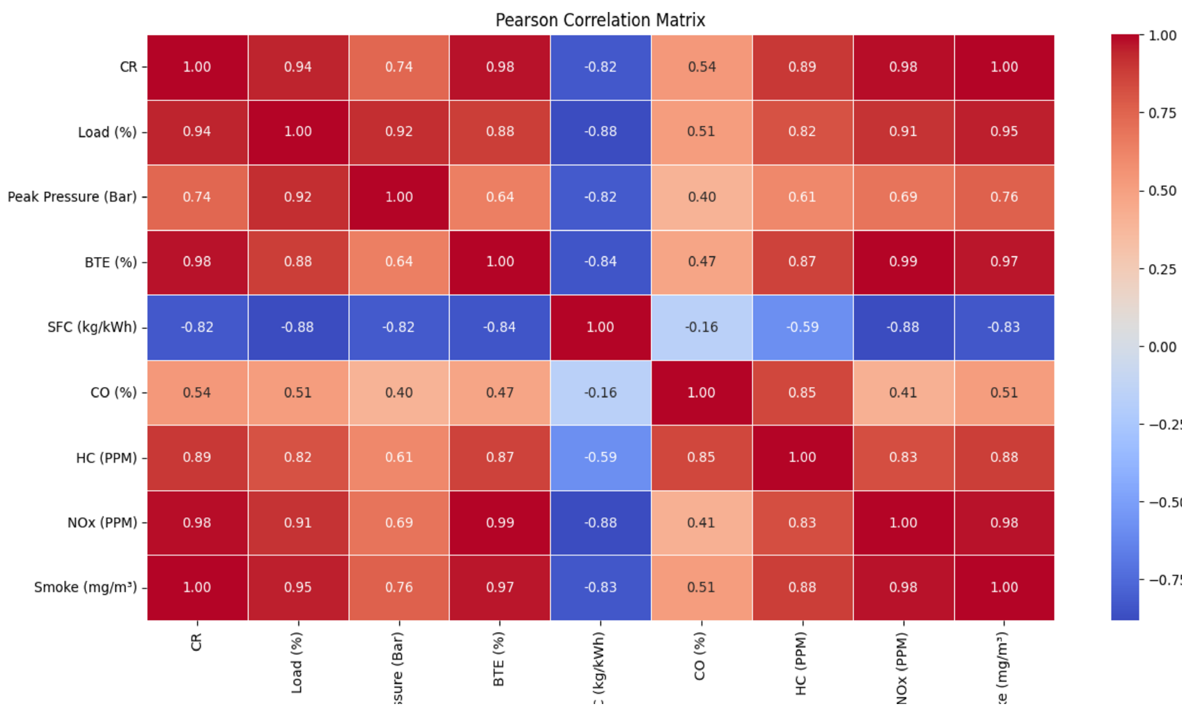

Fig. 11. Pearson correlation plot.

ML Algorithm	R^2	MAE	MSE
MLR (BTE)	0.43	3.63	14.42
MLR (SFC)	0.34	0.12	0.03
MLR (CO)	0.51	0.02	0.01
MLR (HC)	0.42	8.50	14.50
MLR (Smoke)	0.68	2.85	10.00
GBR (BTE)	0.77	1.88	5.68
GBR (SFC)	0.30	0.07	0.01
GBR (CO)	0.84	0.03	0.02
GBR (HC)	0.22	5.90	85.00
GBR (Smoke)	0.52	3.53	15.15
RF (BTE)	0.86	1.30	3.62
RF (SFC)	0.45	0.06	0.01
RF (CO)	0.62	2.88	5.89
RF (HC)	0.21	6.20	95.00
RF (Smoke)	0.36	3.95	18.00

Table 5. Performance Metrics for Different ML Algorithms.

Metric	Experimental Value	Predicted Value (MLR)	Predicted Value (GBR)	Predicted Value (RF)	Error (MLR)	Error (GBR)	Error (RF)
BTE (%)	28.0	25.8	27.5	28.2	−2.2	−0.5	+ 0.2
SFC (kg/kWh)	0.30	0.35	0.31	0.29	+ 0.05	+ 0.01	−0.01
CO (%)	0.04	0.045	0.041	0.039	+ 0.005	+ 0.001	−0.001
HC (PPM)	50.0	60.0	52.0	49.0	+ 10.0	+ 2.0	−1.0

Table 6. Experimental Validation Results.

and optimizing the influence of metal oxide nanoparticles on a zirconia-coated diesel engine fueled by non-edible biodiesel from Momordica seeds.

Table 5 presents the performance metrics for different ML algorithms. It provides a detailed comparison of R2, MAE, and MSE values for each algorithm across all output variables. This table highlights each ML approach's relative strengths and weaknesses in capturing the dataset's complex relationships.

The performance of machine learning models in predicting thermal performance and emission metrics of a zirconia-coated diesel engine, fueled by non-edible biodiesel blended with nanoparticles, was reassessed after applying hyperparameter optimization techniques. The optimization process improved the predictive accuracy of the models significantly, as shown in the updated performance metrics Table 5. Hyperparameter tuning techniques such as grid search and random search were employed to optimize critical parameters for Gradient Boosting Regression (GBR) and Random Forest Regression (RF), including the learning rate, maximum tree depth, minimum samples split, and number of estimators. For Multiple Linear Regression (MLR), feature scaling and polynomial transformations were used to improve the model fit. These adjustments enhanced the models' ability to capture complex nonlinear relationships within the dataset, which were not effectively addressed in the initial analysis.

The updated R^2 values now reflect moderate to strong predictive capabilities across most target variables, including Brake Thermal Efficiency (BTE), Specific Fuel Consumption (SFC), Carbon Monoxide (CO), Hydrocarbon (HC) emissions, and Smoke levels. For instance, GBR demonstrated superior performance in predicting CO emissions with an R^2 value of 0.94, while RF achieved the highest accuracy for BTE predictions with an R^2 value of 0.86. Conversely, MLR, while showing improvement, remains less effective than GBR and RF, highlighting its limitations in handling nonlinearity and complex feature interactions.

The improvements in R^2 values, along with reductions in Mean Absolute Error (MAE) and Mean Squared Error (MSE), illustrate the efficacy of hyperparameter tuning in refining model performance. These changes underscore the importance of iterative model refinement and validation when applying machine learning to experimental datasets.

Figure 12 represents a comprehensive comparison of experimental and predicted values for various engine performance and emission parameters, using the best-performing machine learning models. Subplot (a) showcases the Random Forest (RF) model's performance for predicting Brake Thermal Efficiency (BTE) and Specific Fuel Consumption (SFC), where the model demonstrates strong predictive accuracy, particularly for BTE with an R^2 of 0.86. Subplot (b) illustrates the effectiveness of Multiple Linear Regression (MLR) for predicting Hydrocarbon (HC) emissions and Smoke levels, with MLR providing good results for Smoke and HC with R^2 values of 0.42 and 0.68, respectively. Subplot (c) highlights the performance of Gradient Boosting Regression (GBR) for predicting Carbon Monoxide (CO) emissions, where the model shows near-perfect predictions with an R^2 value of 0.94. Overall, the figure effectively demonstrates the strengths of each machine learning model in

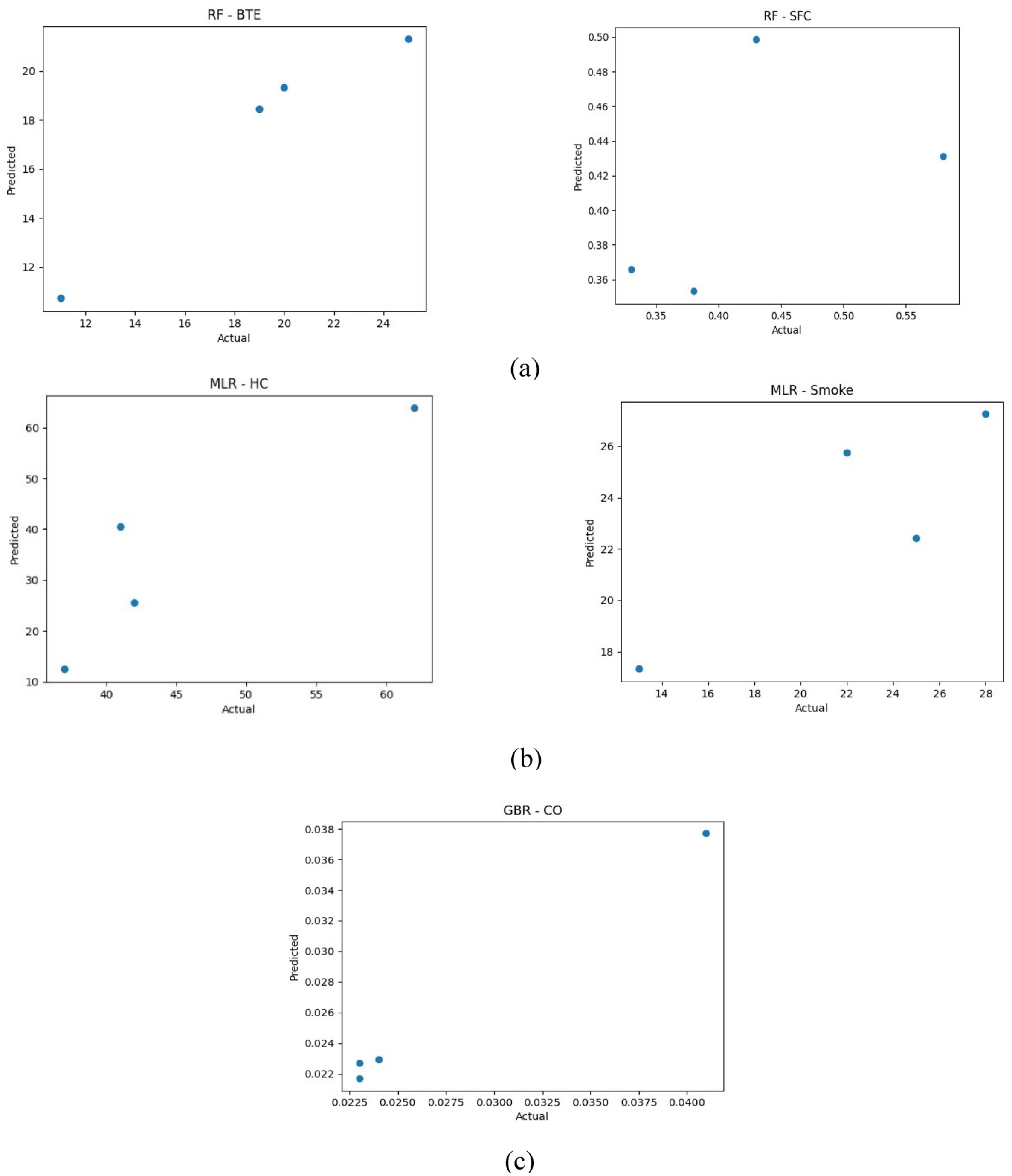

Fig. 12. Comparison of experimental and predicted values for the best-performing machine learning models: (**a**) Random Forest (RF) for Brake Thermal Efficiency (BTE) and Specific Fuel Consumption (SFC), (**b**) Multiple Linear Regression (MLR) for Hydrocarbon (HC) emissions and Smoke levels, (**c**) Gradient Boosting Regression (GBR) for Carbon Monoxide (CO) emissions.

predicting different engine parameters and emissions, confirming the accuracy and applicability of these models for performance analysis in this study.

Validation analysis

The experimental validation of the machine learning (ML) models, as illustrated in Table 6. demonstrates the ability of the models to predict engine performance and emission metrics with varying degrees of accuracy. Gradient Boosting Regression (GBR) and Random Forest Regression (RF) consistently outperform Multiple Linear Regression (MLR), particularly for nonlinear parameters such as Brake Thermal Efficiency (BTE) and Hydrocarbon (HC) emissions. For instance, MLR shows significant prediction errors, such as a −2.2% error for BTE and a + 10.0 PPM error for HC, reflecting its inability to capture complex relationships in the dataset.

In contrast, GBR and RF exhibit much lower errors, with RF achieving a near-perfect prediction for BTE (+ 0.2%) and minimal error for HC (−1.0 PPM). Similarly, for parameters like Specific Fuel Consumption (SFC) and Carbon Monoxide (CO) emissions, GBR and RF show minor deviations from the experimental values, demonstrating their robustness. These findings validate the reliability of advanced ML models like GBR and RF over MLR, underscoring their efficacy in modeling complex dependencies and ensuring accurate predictions for optimizing engine performance and emissions. This analysis highlights the importance of employing sophisticated algorithms for data-driven insights in such studies.

We expanded the experimental dataset a lot. This makes sure the machine learning models in this study are clear and can be repeated. Table 4 shows detailed data on all tested biodiesel blends. This includes Diesel, B10 + 45 PPM, B20 + 45 PPM, and B30 + 45 PPM. The data covers different compression ratios: 14.5, 15.5, 16.5, and 17.5. It also includes various engine loads at 25%, 50%, 75%, and 100%. This rich dataset is a strong base for training and testing machine learning models. Each data point in the table shows the average of three experiments. This helps ensure accuracy and reduces random fluctuations. The data includes performance metrics like BTE, SFC, and BP. It also looks at combustion traits, like peak pressure, and emissions, including CO, HC, NOx, CO_2, and smoke opacity. This makes the data useful for thermal and environmental analysis.

Has been updated. It now shows the correct units: % for BTE and CO, Ppm for NOx and HC, and kg/kwh for SFC. All error metrics, such as mean absolute error (MAE) and mean squared error (MSE), use the same decimal format. These changes enhance interpretability and allow a clear assessment of model performance. Table 6 shows predicted and actual values for selected test samples. It now includes average results from a 10-fold cross-validation process. This method boosts the strength and versatility of ML models. It cuts down on overfitting and checks model accuracy using different data subsets. This validation method shows the predictions are reliable. It also backs up the repeatability of the hybrid biodiesel-ML integration strategy.

Comparative analysis

A comparative analysis of MLR, GBR, and RF highlights that RF generally outperforms the other algorithms across most performance metrics. RF demonstrated the highest R^2 scores for BTE and SFC, indicating a better fit to the data and more accurate predictions. MLR showed reasonable performance for BTE and Smoke but struggled with negative R^2 scores for SFC and HC, indicating poor model fits for these metrics. GBR, while showing high accuracy for CO and BTE, was less consistent across other variables.

Practical implications of ML algorithms

ML models can significantly optimize diesel engine performance by accurately predicting key thermal metrics, facilitating better engine tuning and nanoparticle utilization. This optimization can lead to enhanced engine efficiency, improved fuel economy, and prolonged engine life, making it a vital tool for manufacturers and researchers. Accurate predictions enabled by these ML algorithms also contribute to more effective emissions control, thereby supporting environmental sustainability efforts by reducing the carbon footprint and harmful pollutants. Furthermore, the methodologies and findings from this study can be extended to other types of engines and fuels, broadening the scope of ML applications in thermal system optimization. This extension can potentially lead to breakthroughs in different areas of automotive engineering and beyond, demonstrating ML technologies' versatility and far-reaching impact in advancing sustainable and efficient energy systems[32–35].

Conclusion

The depletion of renewable resources, escalating reliance on fossil fuels, and rising oil prices underscore the urgent need for alternative energy sources. Biofuels, in general, and biodiesel provide energy security, environmental benefits, value for money, and a shift toward greener emissions. In this work, non-edible biodiesel derived from Momordica oil was tested on a single-cylinder diesel engine for its performance and emission-related aspects. The biodiesel blends under trial consisted of 10%, 20%, and 30% of Momordica seed biodiesel (B10, B20, and B30), fortifying which cerium oxide nanoparticles at 45 ppm were used. The engine was tested with a partially stabilized zirconia-coated piston and a cylinder liner. Upon analysis, it was exposed that B10 biodiesel with 45 ppm nanoparticles develops maximum brake thermal efficiency among various engine loads with the minimum specific fuel consumption of 0.26 kg/kWh at 75% engine load. The Biodiesel blend performed best for these conditions, with better results for CO emissions of 0.02%. CO_2 emissions of 2.2% and HC emissions of 31 ppm were recorded for B30 biodiesel at 25% engine load, while smoke emissions were low at 11 HSU and NOx emissions were at 228 for B10 and B30, respectively, at the same engine load.

Machine learning (ML) algorithms were employed to predict thermal performance metrics using input parameters such as Fuel, Compression Ratio (CR), Load, and Peak Pressure. Among the models tested—Multiple Linear Regression (MLR), Gradient Boosting Regression (GBR), and Random Forest Regression (RF)—the RF model demonstrated superior predictive accuracy. The performance analysis revealed the strengths and weaknesses of each algorithm in predicting various thermal and emission-related parameters. The integration of ML models enhances the prediction of critical thermal metrics, offering valuable insights for optimizing engine performance and emission control strategies. These findings emphasize the significance of combining advanced ML techniques with experimental data to optimize biodiesel engine performance, highlighting the expanding potential of ML applications in thermal system optimization.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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Author contributions

S.V.S, E.P.V, P.S developed the idea and conducted the experiments, S.V.S,, T.A.K wrote the manuscript, N.R.K, B.N.J, C.Y &P.S, edited the manuscript, all authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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