

Synergistic effects of magnesium oxide nanoparticles on B30 waste cooking oil biodiesel: Performance optimization and artificial neural network modeling

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Abstract

The growing demand for clean energy has intensified interest in alternative fuels like biodiesel. In this work, waste cooking oil (WCO) was utilized as a low-cost, sustainable feedstock for biodiesel production. The produced biodiesel was tested in a two-cylinder diesel engine operating at 1500 rpm under various load conditions, focusing on the B30 blend. To enhance performance, magnesium oxide nanoparticles (nano-MgO) were added to the B30 blend at concentrations of 10, 30, and 60 ppm. Experimental results demonstrated that the B30 blend provided balanced engine performance. The incorporation of nano-MgO enhanced combustion characteristics, leading to improved brake thermal efficiency by (3.52% increase) and lower brake-specific fuel consumption by (11% reduction) with the use of B30 + 60 ppm MgO, compared with untreated biodiesel. Emission analysis revealed a noticeable decline in major regulated pollutants (including a 30% reduction in CO, 26% reduction in HC, 24.3% reduction in NO_x, and 33% reduction in smoke opacity with B30 + 60 ppm MgO) driven by the catalytic influence of nano-MgO, which promotes oxygen availability for complete combustion. Additionally, a multi-output artificial neural network (ANN) based on Bayesian regularization was developed to predict engine performance and emissions. The model achieved high predictive accuracy, with an average test coefficient of determination (R^2) of approximately 0.9439 across all outputs. Parity and sample-based assessments confirmed its robustness under different operating conditions, validating the developed ANN as an efficient tool for performance prediction and optimization.

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1. Introduction

Modern societies rely heavily on diverse energy sources to sustain economic growth. Because fossil fuels are not renewable, their reserves are running out. Fossil fuels are also linked to environmental and ecological problems, such as global warming. Non-renewable conventional energy resources are still predominantly used to meet countries' energy demands. Therefore, finding suitable substitutes for these conventional fuels is critically important.

Renewable energy is defined as energy that mostly comes from natural sources, such as the sun, biomass, wind, geothermal, tidal energy, and hydropower. The ideal alternative to fossil fuels is biomass because it is renewable, produces fewer emissions (such as carbon dioxide, carbon monoxide, nitrogen oxides, sulfur oxides, smoke, etc.), and is less expensive than traditional fossil fuels. The usage of these alternative energies is currently being emphasized in several nations [1]. However, biomass is available in diverse forms and can be stored and used at any time of the year for energy production. The seasonality of wind and solar energy sources can be lessened by using biomass as a hybrid supplement. Fuels produced from organic materials, such as animal waste and

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plant matter, are known as biofuels. Biofuels and other alternative fuels can produce electricity, heat houses, and power vehicles. Seeds, kernels, leaves, agricultural leftovers, sewage waste, forest residue, human waste, and animal excrement are a few examples of the different types of biomass feedstocks. Biomass is therefore a sustainable and renewable source of green energy [2]. Because they can lower greenhouse gas emissions and the need for fossil fuels, biofuels are being researched extensively as an alternative energy source. However, their widespread use endangers biodiversity, land use, and food security. Among the feedstocks utilized in biofuels are intensive agricultural inputs, which have been connected to environmental deterioration and deforestation. They can also compete with food crops, potentially escalating prices and worsening food insecurity [3]. To mitigate these sustainability concerns, waste cooking oil (WCO) has emerged as a promising, non-edible alternative. Among the diverse production pathways for converting such feedstocks, transesterification stands out as the most commercially viable method. Within this process, heterogeneous catalysts are systematically preferred over their homogeneous counterparts due to their excellent recyclability and significantly mitigated corrosion risks. Biodiesel and petroleum-based diesel have many physical and chemical properties. Biodiesel is made from biodegradable, reusable, and low-toxicity biomass feedstock. It can be used in blended or raw form, with or without mechanical modifications, in diesel engines that are currently in use. Biodiesel improves engine performance because it emits less carbon monoxide and particulate matter, extends an engine's operating life due to its lubricating properties, and is less volatile due to its higher boiling point, making it easier to transport and store [4]. Its higher flash point also improves handling and storage safety. Biodiesel is often considered carbon-neutral because the CO₂ released during combustion is approximately balanced by the CO₂ absorbed during biomass growth. Despite these advantages, the use of neat biodiesel often leads to a notorious 'biodiesel NO_x penalty' due to its inherent oxygen-rich structure which promotes higher peak flame temperatures during the premixed combustion phase. This thermal trade-off necessitates the development of effective mitigation strategies, such as fuel-borne nano catalysts.

On the other hand, utilizing biodiesel in traditional diesel engines has several disadvantages, such as poor performance in cold weather, ineffective fuel atomization, piston ring sticking, relatively high density, and a drop in fuel economy. However, these drawbacks can be mitigated using high-energy nanoadditives, which are added in trace amounts to improve combustion efficiency and fuel stability [5]. Such additives offer advantages including low dosage requirements, corrosion resistance, reusability, as well as improved sustainability. Researchers looked into how nanoparticles affected the characteristics of biodiesel. Among the nanoparticles that have been evaluated for their ability to enhance fuel characteristics and engine performance are carbon nanotubes, titanium oxide, magnesium oxide, zinc oxide, graphene, cerium oxide, and aluminum oxide [6-8] as well as other hybrid carbon-based materials [9]. Specifically, zinc oxide nanoparticles have demonstrated remarkable potential in improving thermal performance and reducing hazardous smoke emissions [10]. Additionally, Nachippan, Balaji [11] demonstrated the effectiveness of nano-MgO in enhancing the performance of cottonseed biodiesel. While carbon-based and metal-oxide nanoadditives have been widely reported to enhance brake thermal efficiency (BTE) as well as reduce harmful emissions over various engine configurations [12-14], magnesium oxide (MgO) nanoparticles offer distinct physicochemical advantages over other metal oxides. Compared with cerium oxide, magnesium oxide can be produced more easily and sustainably [15-18]. Zinc oxide is another studied nanoadditive [19-21]; however, its more complicated processing requirements make MgO nanoparticles a more attractive option for biodiesel applications due to production efficiency, cost-effectiveness, and environmental compatibility. The specific catalytic mechanism of nano-MgO relies on its behavior as an effective oxygen-donating catalyst with a basic surface and high surface-area-to-volume ratio, which promotes critical interfacial fuel processes, enhances atomization, and improves overall combustion efficiency. This catalytic activity significantly lowers carbon monoxide emissions by promoting more complete oxidation of hydrocarbon molecules, converting CO to CO₂, while its coupling effect in transesterification highlights its stability as a heterogenic nano catalyst. Furthermore, nano-MgO significantly influences the heat transfer and thermal conductivity within the combustion chamber. Due to its high inherent thermal stability, the addition of MgO nanoparticles improves the in-cylinder thermal conductivity and controls the combustion

parameters. This enhanced thermal conductivity reduces peak in-cylinder temperatures and alters heat transfer characteristics, leading to a noticeable decline in thermal nitrogen oxide (NO_x) emissions. Previous literature has demonstrated the capabilities of nano-MgO in distinct configurations; for instance, Nachippan et al. [11] successfully proved the effectiveness of nano-MgO in enhancing the performance and emission characteristics of cottonseed biodiesel. Similarly, Farouk, Tayeb [22] established that synthesis via MgO nano catalysts results in enhanced engine performance and reduced exhaust emissions.

Despite these extensive studies, limited research has focused on the synergistic effects of MgO nanoparticles in B30 waste cooking oil biodiesel, particularly considering combined performance, emission, and closed-loop circular economy sustainability aspects. To contextualize these research gaps, Table 1 evaluates various carbon-based and metal-oxide nanoadditives widely reported to enhance brake thermal efficiency (BTE) and reduce harmful emissions. However, while candidates like GO, Al₂O₃, and TiO₂ improve engine parameters, they are often constrained by high synthesis costs, chemical complexity, or environmental toxicity risks. In contrast, magnesium oxide (MgO) nanoparticles offer a superior alternative, effectively addressing these limitations through excellent cost-effectiveness, environmental friendliness, and ease of production. These findings further support the strategic selection of MgO nanoparticles in the present investigation, as MgO exhibits comparable catalytic activity and thermal stability, especially when applied to B30 waste cooking oil biodiesel.

Table 1. Performance and emissions of diesel and biodiesel fuels mixed with nanoadditives based on carbon and metal oxides

Nanoadditi vs	Fuel Blend	Engine Type	Main Performance Effects	Emission Reduction	Referen ce
CeO ₂	B10+3% water+100 ppm CeO ₂	Single- cylinder diesel	(4.5-8%)BTE	(12 -25%) CO, (10 -20%) NO _x	[15]
GO + Butanol	B25(Nigell) + 90 ppm GO	CRDI diesel	(3-6.5%) BTE	(15 -30%) CO, (8 -18%) NO _x , (12 -25%) Smoke	[12]
CoO	B20(Waste oil)+50ppm CoO	Urea-SCR diesel	(3.5-7%) BTE	(10 -24%) CO, (12 -22%) NO _x	[17]
Al ₂ O ₃	B20(Waste Oil)+ 100 ppm Al ₂ O ₃	CRDI diesel	(4.-8.5%) BTE	(12 -28%) CO, (10 -19%) NO _x	[19]
CNT	B20(Palm) + 50 ppm CNT	Single- cylinder DI diesel	(5-9.5%) BTE, improved combustion	(15 -32%) CO, (14 -28%) HC, (18 -35%) Smoke	[23]
GO	B20(Soybe) +100 ppm GO	VCRsingle- cylinder diesel	(3.5-7.2%) BTE	(15 -27%) Smoke, (14- 30%)CO, (9 -20%)NO _x ,	[13]
GNP	B20 (Jatropha)+ 75 ppm GNP	Turbochargd DI engine	(4-8%) BTE, faster ignition	(18 -33%)CO, (10 - 22%)NO _x	[24]
ZnO	B25(Soybe) + 50 ppm ZnO	VCRsingle- cylinder	(3.8-7.5%) BTE	(12 -26%) CO, (11 -21%) NO _x , (14 -30%) Smoke	[25]
TiO ₂	B30+75pp m TiO ₂	Single- cylinder DI	(3.2-6.8%) BTE	(16 -31%) HC, (20 -38%) Smoke	[26]

Due to the highly non-linear, coupled, and multivariable nature of combustion and exhaust emission chemistry in compression ignition engines under varying loads, traditional thermodynamic and analytical modeling approaches often fall short in real-time predictions.

Consequently, black-box modeling tools, especially artificial neural networks (ANNs), have emerged as highly efficient digital surrogates. Process models are generally classified as either linguistic or mathematical. The linguistic approaches, in particular black-box models, can play an important role when system behavior is too complex to be captured through analytical methods. These models focus on linking inputs to outputs without the necessity to explicit knowledge of underlying mechanisms. This characteristic makes them especially suitable for various systems characterized by nonlinearity, multivariable interactions, and incomplete physical understanding. Among black-box approaches, artificial neural networks (ANNs) have gained increasing attention due to their ability to learn from data, assimilate large volumes of system information as well as accurately simulate real-world responses while remaining computationally efficient. Inspired by biological neural systems, ANNs function as distributed information-processing frameworks capable of prediction, adaptation, and operation in complex environments where conventional mechanistic or kinetic models are impractical or unreliable. Although highly system-specific and not readily transferable between applications, ANN models are particularly attractive for real-time control, process optimization, and fitting complex kinetic behavior, as demonstrated in many recent applications, where traditional mathematical modeling proves extremely challenging [27-29]. It is hypothesized that the integration of MgO nanoparticles into high-viscosity B30 waste cooking oil biodiesel will physically improve fuel droplet atomization and chemically act as an oxygen donor, thereby facilitating cleaner combustion while simultaneously reducing the fuel consumption penalty. This study aims to systematically evaluate the effects of MgO nanoparticles at concentrations of 10, 30, and 60 ppm on the combustion, performance, and emission characteristics of B30 waste cooking oil biodiesel in a constant-speed diesel engine under varying loads. In addition, all process responses were simultaneously predicted and optimized using an artificial neural network (ANN) model trained on the experimental dataset. This enables data-driven evaluation without reliance on explicit mechanistic assumptions. It also provides a comprehensive evaluation of the ANN's multi-output predictive capability.

2. Materials and Methods

2.1 Production Process of Biodiesel

Waste cooking oil belongs to the triglyceride family, which is similar to virgin vegetable oils and animal fats. It is a feedstock for biodiesel that is chemically comparable to virgin oils, but it undergoes compositional changes during frying. It is a cheaper and more sustainable feedstock for biodiesel production. The materials used in this study are waste cooking oil, methanol, and sodium hydroxide (NaOH) as a catalyst.

The biodiesel production process consisted of three main steps: pretreatment, transesterification, and distillation. First, raw waste cooking oil (WCO) with a high initial free fatty acid (FFA) content of 4.12 wt.% went through a rigorous pretreatment stage. The oil was heated to 80°C for 45 minutes under continuous stirring, passed through a 5-micron stainless steel mesh filter to remove solid impurities, and left in a separating funnel for 24 hours to settle. The upper oil layer was then collected and dried at 105°C under vacuum for 60 minutes. This thermal and vacuum process successfully stripped out trace moisture and volatile components, lowering the effective FFA level down to 0.25 wt.% before the chemical reaction. Under these low-FFA conditions, the alkali-catalyzed transesterification could proceed efficiently without any significant soap formation. The transesterification reaction was performed in a three-necked flask fitted with a thermometer, a reflux condenser, and a magnetic hot-plate stirrer. The chemical formulation used an optimized 1:6 oil-to-methanol molar ratio, which combined 4 L of pretreated WCO with 1 L of high-purity methanol, and a 1.25 wt.% NaOH catalyst loading (50 g of NaOH based on the total mass of the oil). The mixture was reacted at a constant temperature of 65°C under continuous magnetic stirring at 600 rpm for 60 minutes. From a chemical kinetics perspective, this specific formulation and high-shear stirring minimized mass-transfer resistance between the immiscible liquid phases, driving the alcoholysis of triglycerides toward forward conversion and achieving a final biodiesel yield of approximately 88%, which was calculated using the mass balance framework expressed in Equation 1.

$$\text{Biodiesel Yield (\%)} = \left(\frac{\text{Mass of purified biodiesel (g)}}{\text{Mass of pretreated oil (g)}} \right) \times 100 \quad (1)$$

The reaction mechanism for converting triglyceride ester bonds into fatty acid methyl esters and glycerol byproducts is shown in Equation 2. The complete production sequence and the transesterification experimental setup are illustrated in Fig. 1 and Fig. 2, respectively, while the properties of the raw waste cooking oil are summarized in Table 2.

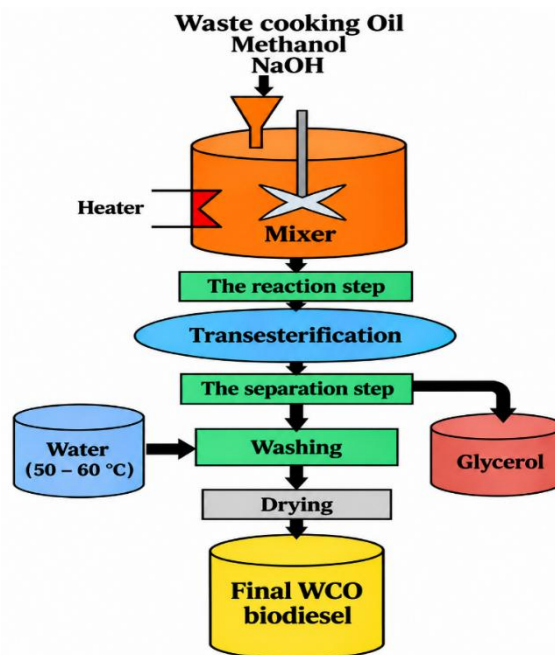
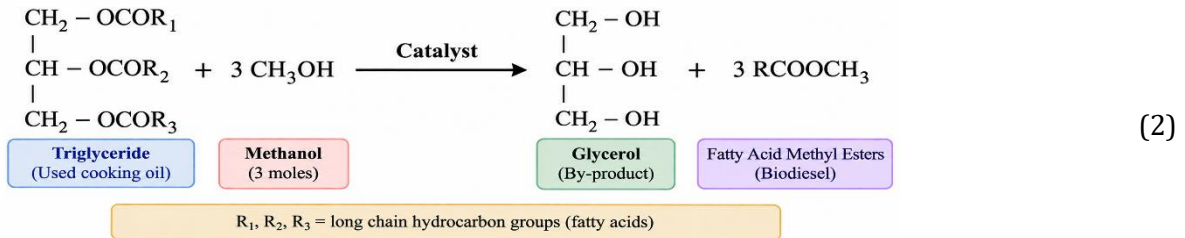


Fig. 1. Flow diagram of the biodiesel production process [9]

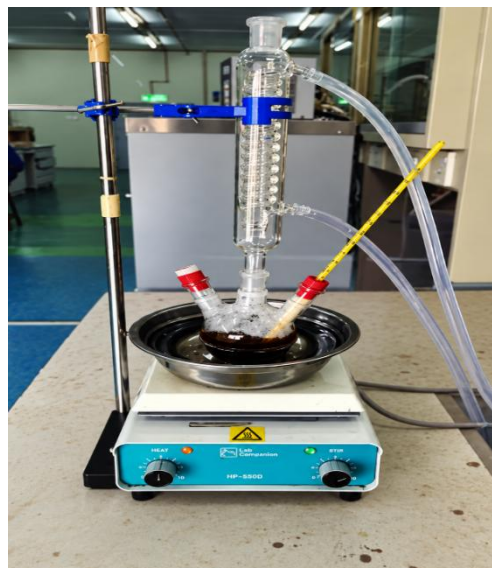


Fig. 2. The transesterification experimental setup

Table 2. Waste cooking oil properties

Property	ASTM Standard	Value
Free fatty acid (FFA, wt.%)	ASTM D5555	4.12
Density (kg/m ³)	ASTM D1298	918
Kinematic viscosity @ 40 °C (mm ² /s)	ASTM D445	41.3
Calorific value (MJ/kg)	ASTM D240	39.2
Flash point (°C)	ASTM D92	244
Fire point (°C)	ASTM D92	276
Cloud point (°C)	ASTM D2500	9
Pour point (°C)	ASTM D97	3
Moisture content (wt.%)	ASTM D6304	0.46

2.2 Nanoadditive (MgO)

Magnesium oxide (MgO) is an inorganic compound naturally occurring as a hygroscopic solid and commonly known as magnesia. Structurally, MgO consists of Mg²⁺ and O²⁻ ions and arranged in a cubic ionic (rock-salt) lattice. Magnesium oxide nanoparticles are non-toxic, odorless, and chemically stable. They have high melting point as well as hardness. This makes them suitable for high-temperature applications. Due to its high thermal stability and basic surface characteristics besides its catalytic activity, MgO has been widely investigated for fuel and combustion-related applications. When added into diesel-biodiesel fuel blends, MgO nanoparticles can act as combustion-enhancing additives. This is likely due to its capability to promote oxidation reactions, improve flame stability, and facilitate more complete fuel-air interaction. These properties may contribute in improvement of combustion efficiency and reduction of pollutant formation. The physicochemical properties of magnesium oxide used herein are listed in Table 3. To mix the MgO nanoparticles uniformly into the biodiesel, a Drawell probe sonicator (China, 20–25 kHz) with a 250 W nominal capacity was used. The device was fitted with a 13 mm titanium alloy probe tip and operated at a 60% amplitude for 30 minutes. To prevent heat buildup during the processing time, the unit was run in intermittent pulse cycles (5 seconds on and 2 seconds off) while keeping the mixture vessel inside an ice-chilled water medium. This successfully kept the temperature of the fuel mixture below 30°C to ensure optimal dispersion phase stability. Sodium dodecyl sulfate (SDS) was added at 0.03 wt.% to stop the nanoparticles from clumping together. Preliminary tests showed that adding 0.03 wt.% SDS alone (without MgO) had no noticeable effect on engine performance or emissions compared to pure B30. This confirms that the surfactant only serves to keep the nanoparticles suspended without affecting the combustion results over a 7-day period.

Table 3. Physicochemical properties of magnesium oxide (MgO)

Purity (%)	≥ 99
Appearance	White solid
Crystal structure	cubic
Molecular Weight (g/mol)	40.3
Density (g/cm ³)	3.58
Surface Morphology	Spherical
Average Particle Size (nm)	30
Specific Surface Area, BET m ² /g	60
Melting Point (°C)	2852
Boiling Point (°C)	3600

2.3 Properties of Waste Cooking Oil Biodiesel (WCOB)

The physicochemical properties of neat biodiesel and MgO nanoparticle-modified biodiesel fuels were determined in accordance with ASTM standard test methods. These properties were evaluated to assess their influence on fuel performance and exhaust emissions when used in a compression ignition (CI) engine. Different MgO nanoparticle concentrations were assessed to study their effects on fuel characteristics and engine behavior. The main goal of this analysis was

to identify variations in fuel properties resulting from the addition of MgO nanoparticles and to evaluate the influence of additive concentration. Engine performance obtained using various biodiesel fuel samples was compared with that of conventional diesel fuel. The measured properties of waste cooking oil biodiesel blends, with and without nanoadditives, are summarized in Table 4. Compared with diesel fuel, the kinematic viscosity of the fuel increased with increasing biodiesel content. The academic innovation of this study relies on the theoretical interaction between the basic surface sites of nano-MgO and the high free fatty acid (FFA) profile (4.12 wt.%) of waste cooking oil. At high in-cylinder temperatures, nano-MgO acts as a cracking catalyst that breaks down heavy fatty acid chains into lighter, volatile fractions, which suppresses soot formation and lowers real-time viscosity. Furthermore, the selection of the B30 blend serves a clear physical purpose; lower blends (B10, B20) do not maximize renewable substitution, while higher blends (B100) suffer from excessive viscosity (5.5 mm²/s) and lower calorific value (38.5 MJ/kg). Therefore, B30 provides the optimized baseline offering a balanced cetane number (54) and density (855 kg/m³) that match standard injection dynamics without engine modifications, while allowing nano-MgO to fully exert its oxygen-donating effects.

However, the addition of MgO nanoparticles to fuel improved its flow characteristics by reducing the viscosity of the biodiesel blends toward values closer to those of conventional diesel. The cetane number of the waste cooking oil biodiesel blends exhibited an increasing trend with higher biodiesel blending ratios, whereas their calorific value demonstrated a corresponding decline. The flash point, which shows a fuel's propensity to ignite, also increased with higher biodiesel content and nanoadditive dosage. Higher flash and fire point values indicate improved handling and storage safety. The observed 10°C rise with MgO nanoparticle addition is realistically governed by the basic porous surface sites of the nanoparticles adsorbing residual free methanol from the synthesis stage, alongside the SDS surfactant establishing an interfacial barrier that slows down the escape rate of volatile fractions [22]. MgO nanoparticle-enhanced biodiesel blends may be regarded as safer than the comparable base fuels since fuels with flash points higher than ambient temperature are safer to handle and transport.

Table 4. Properties of waste cooking oil biodiesel and MgO nanoparticle-enhanced biodiesel blends

Fuel Sample	Kinematic Viscosity @40°C (mm ² /s)	Calorific Value (MJ/kg)	Density (kg/m ³)	Cetane Number	Flash Point (°C)	Fire Point (°C)
D100 (Diesel)	2.8	43	836	48	58	70
B10	3.4	41.5	843	50	75	90
B20	3.8	40.5	848	52	95	115
B30	4.4	39.6	855	54	110	130
B30 + 10 ppm MgO	4.35	40	855.01	57	115	135
B30 + 30 ppm MgO	4.3	40.2	855.03	58	118	140
B30 + 60 ppm MgO	4.22	40.3	855.06	60	120	145
WCO Biodiesel (B100)	5.5	38.5	890	60	160	190

The kinematic viscosity, calorific value, density, cetane number, flash point, and fire point were experimentally measured in accordance with ASTM D445, ASTM D240, ASTM D1298, ASTM D613, ASTM D93, and ASTM D92, respectively. All reported fuel properties represent the definitive mean values calculated from experimental tests conducted systematically in triplicate, with the comprehensive experimental uncertainty analysis for the measurements detailed within Section (2.4).

2.4 Experimental Setup

All experiments were conducted on a two-cylinder, four-stroke, water-cooled diesel engine (Lombardini LDW 502) mounted on an engine test bench. This engine features an indirect injection (IDI) configuration with a pre-combustion chamber design, which fundamentally influences the fuel-air mixing and emission formation mechanisms (specifically NO_x and soot). The engine has a

total cylinder displacement of 505 cc, a compression ratio of 22.8:1, a cylinder bore of 72 mm, and a stroke length of 62 mm. Comprehensive technical attributes of the test engine are detailed in Table 5. The experiments were carried out at a constant engine speed of 1500 rpm. Water was used as the working fluid in the cooling system, circulating through the cylinder water jackets at a controlled temperature of 80°C. The fuels tested in this study were conventional diesel fuel (D100) and waste cooking oil biodiesel blends (B10, B20, and B30), corresponding to 10%, 20%, and 30% volumetric blending ratios, respectively. Engine loading conditions ranged from no load to full load at five intervals: 0%, 25%, 50%, 75%, and 100%. A schematic representation of the experimental engine setup is shown in Fig. 3. Exhaust emissions, including nitrogen oxides NO_x, carbon monoxide (CO), and unburned hydrocarbons (HC), were measured using an exhaust gas analyzer (HPC501, China). Smoke opacity was measured using an AVL smoke meter (415 S, Austria).

Table 5. Technical specifications of the Lombardini LDW 502 test engine

Engine Parameter	Specification and Operational Value
Engine Manufacturer / Model	Lombardini LDW 502 (FOCS Series), Italy
Engine Configuration	4-stroke, Liquid-cooled Diesel Engine
Cylinder Arrangement	2 cylinders in-line, vertical
Fuel Injection System	Indirect Injection (IDI)
Combustion Chamber Design	Pre-combustion chamber (Pre-chamber)
Cylinder Bore × Piston Stroke	72 mm × 62 mm
Total Engine Displacement	505 cc (0.505 L)
Compression Ratio	22.8:1
Intake Aspiration	Naturally aspirated
Maximum Rated Power	8.6 kW (11.7 HP) @ 3600 rpm
Maximum Rated Torque	24.5 Nm @ 2200 rpm
Engine Cooling Medium	Liquid-cooled (water jacket system)

Gaseous exhaust emissions, specifically nitrogen oxides (NO_x), carbon monoxide (CO), and unburned hydrocarbons (HC), were monitored continuously using a calibrated exhaust gas analyzer. At the same time, the smoke density and soot formation limits were recorded via a digital smoke opacity meter connected to the exhaust line. The inlet air mass flow rate was monitored by directing the airflow through a calibrated orifice plate coupled with a U-tube differential manometer. To cancel out aerodynamic pulsations and intake pressure cyclic fluctuations caused by the two-cylinder operation, a 50-liter surge tank was installed upstream of the engine intake manifold, which successfully ensured steady-state manometer fluid displacements. An institutional error analysis was performed to verify the statistical reliability and accuracy of the collected data. The exact measurement ranges, factory accuracy margins, and minimum resolution limits for each sensor and tool are summarized in Table 6.

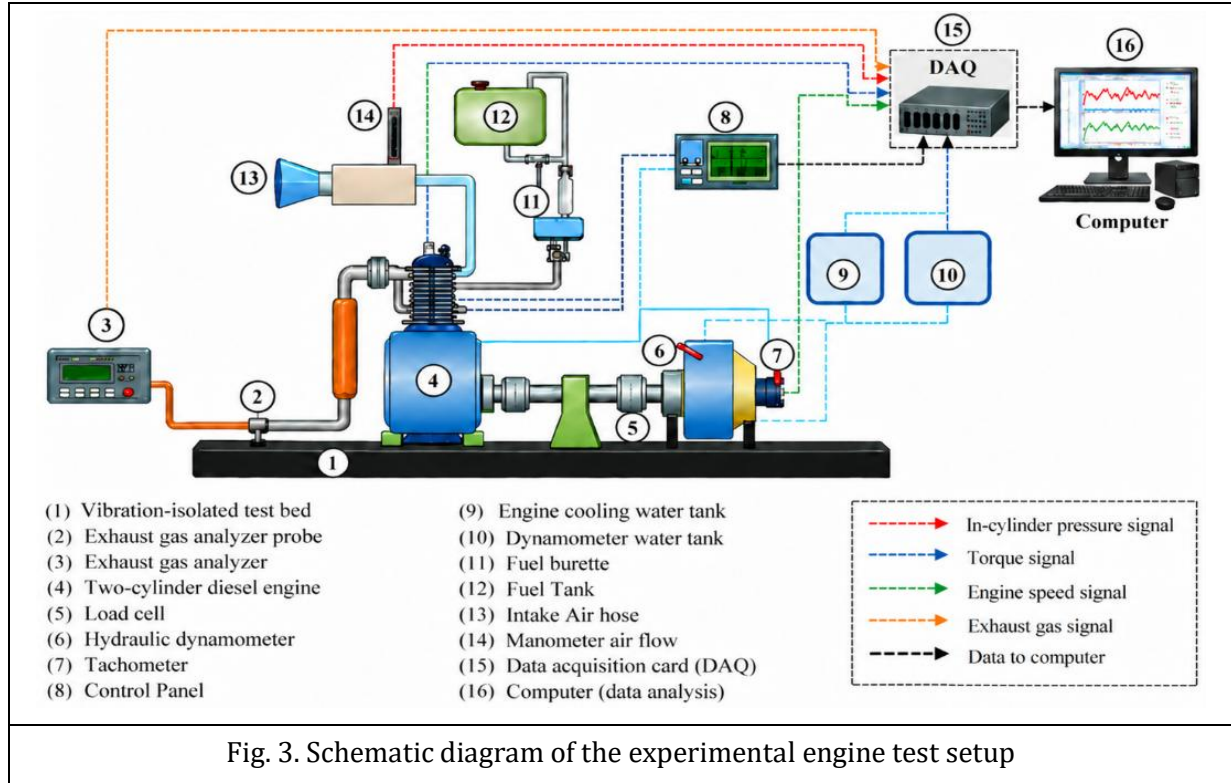
Table 6. Measurement range, accuracy, and resolution of the experimental instruments

Apparatus / Sensor	Measurement Range	Accuracy	Resolution
Gas Analyzer (NO _x)	0–5000 ppm	± 5 ppm	1 ppm
Gas Analyzer (CO)	0–10% vol.	± 0.02% vol.	0.01% vol.
Gas Analyzer (HC)	0–9999 ppm	± 10 ppm	1 ppm
Smoke Opacity Meter	0–100%	± 1%	0.1%
Load Cell (Engine Load)	0–50 kg	± 0.1 kg	0.05 kg
K-type Thermocouples	0–1200 °C	± 1.5 °C	0.1 °C
Fuel Flow Meter	0–500 ml/min	± 0.5%	0.1 ml/min
Air Flow Manometer	0–60 mbar	± 1%	0.5 mbar

The propagation of discrete measurement errors was mathematically determined using the standard Kline and McClintock method to calculate the Total Experimental Uncertainty (U_{total}) based on the percentage uncertainty of each individual variable, according to the following Equation (3):

$$U_{total} = \sqrt{(U_{Temp})^2 + (U_{Load})^2 + (U_{Fuel})^2 + (U_{Air})^2 + (U_{CO})^2 + (U_{HC})^2 + (U_{NOx})^2 + (U_{Smoke})^2} \quad (3)$$

Where U_{Temp} , U_{Load} , U_{Fuel} , U_{Air} , U_{CO} , U_{HC} , U_{NOx} , and U_{Smoke} represent the percentage uncertainties of engine temperature, load, fuel flow rate, air flow rate, and NO_x, CO, HC, and smoke emissions, respectively. Based on the individual accuracy limits and the baseline variances of each measuring unit, the cumulative experimental uncertainty for the complete test campaign was found to be 2.84%. This result is well within the acceptable 5% error margin standard for internal combustion engine research [30].



2.5 Artificial Neural Network

The artificial neural network (ANN) is a parallel and distributed computing model modeled after the architecture of the human brain. Information within the network is processed through interconnected units called as neurons [27, 31]. These neurons are commonly arranged in a configuration with layers. These layers consist of an input layer, one or more hidden layers, and an output layer. At the input layer, data are introduced, which are then altered gradually as they pass through the network. Nonlinear activation functions in the hidden layers enable the model to capture complex patterns that cannot be represented by linear relationships alone. The processed signals will be then forwarded to the output layer. The final predictions are produced in this layer [32, 33]. This makes ANNs effective in particular for modeling highly nonlinear and multivariable systems. The input layer architecture was constructed with a detailed numerical dimensional mapping to represent the operational states and fuel chemistry accurately. Rather than using arbitrary string labels or numerical indices for the different fuel options (D100, B10, B20, B30, B100, and nano-MgO treated blends), the fuel types were numerically codified within the neural space using their distinct, experimentally determined physicochemical properties as distinct input vectors. Specifically, the dynamic input domain for each simulation layout consisted of five baseline independent variables: real-time engine load (0% to 100%), kinematic viscosity, lower calorific value, density, and cetane number. This multi-variable indexing framework allowed the input layer to translate structural chemical differences between pure petroleum diesel, unblended biodiesel, and nano-suspended fluids into quantifiable computational matrices. The main goal is to predict engine performance and emission characteristics under different operating conditions. The input space consisted of engine load (from 0% to 100% full load), and fuel type (eight different blends), which were B10, B20, B30, B100, D100, and B30 mixed with MgO nanoparticles at three

concentrations of 10, 30, and 60 ppm. The network predicted six response variables, which were specific fuel consumption (SFC), brake thermal efficiency (BTE), carbon monoxide (CO), hydrocarbon (HC) emissions, nitrogen oxides (NO_x), and smoke opacity. This multi-output structure enabled the model to learn shared dependencies among performance and emission parameters rather than treating each response independently.

To ensure stable as well as unbiased learning, all input and output variables were normalized to the range of 0-1 using map minmax scaling [29]. This would prevent variables with larger numerical ranges from dominating the training process. The network architecture was based on a multilayer perceptron (MLP) containing two hidden layers. Both linear and nonlinear interactions were effectively captured by employing Tansig activation functions in the hidden layer and a Purelin function in the output layer [34, 35]. Model training and selection were conducted using a nested cross-validation approach, allowing robust evaluation of generalization performance and avoidance of overfitting. Three advanced training algorithms including Levenberg-Marquardt (trainlm), Bayesian regularization (trainbr), and scaled conjugate gradient (trainscg) were systematically examined due to their strong convergence behavior, computational efficiency, and ability to control overfitting compared to conventional gradient-based methods [36]. Hyperparameter optimization was carried out using 5-fold cross-validation [37]. The number of neurons in each of the two hidden layers was varied from 3 to 25. This procedure resulted in 529 possible network configurations for each training algorithm. The optimal architecture was chosen based on the minimum mean squared error (MSE) obtained, which established the selected architecture with 18 and 12 hidden neurons in the first and second hidden layers, respectively.

For network optimization, the dataset was initially divided using an 80/20 partition rule, with 32 samples used for model development and 8 samples kept exclusively for final testing. The 32-sample development subset was further evaluated using 5-fold cross-validation during the network selection process. For each fold, the model was trained using the training portion and evaluated using the corresponding validation portion. The mean and standard deviation of the validation MSE were calculated across the five folds. The best network was then retrained using the complete 32-sample development subset, while the remaining 8 samples were retained as an independent final test set. Finally, the evaluation of the multi-output predictions was validated using mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) metrics.

3. Results and Discussion

3.1 Brake-Specific Fuel Consumptions (BSFC)

A crucial performance indicator for internal combustion engines is brake-specific fuel consumption (BSFC), which shows how well fuel is converted into power; a lower value denotes higher performance and vice versa. BSFC is expressed in (kg/kW.hr). Because there is a strong correlation between rising engine load and the amount of fuel supplied for combustion, the BSFC for all tested fuels decreased progressively from 25% load to full load [38].

Fig. 4 presents the variation of BSFC for all the tested fuel blends at different engine loads and a constant speed of 1500 rpm. Since diesel has a higher calorific value than waste cooking oil methyl ester blends, more biodiesel fuel is traditionally required to produce the same amount of power. However, the empirical profiles reveal a unique thermodynamic trend where the unadditived B30 blend demonstrates a BSFC curve running closer to the conventional diesel (D100) baseline compared to the lower B10 and B20 mixtures. Chemically, while pure biodiesel (B100) carries the highest intrinsic oxygen content, its operation is heavily penalized by excessive kinematic viscosity and lower energy density. Conversely, the B30 configuration achieves an optimized chemical compromise. It features a higher oxygen fraction relative to the lower blends (B10 and B20) which accelerates combustion kinetics and ensures superior air-fuel mixing completeness inside the chamber. This localized chemical availability drives a substantial expansion in the engine's brake thermal efficiency (BTE), effectively offsetting the minor calorific value deficit of the blend and compressing the specific fuel consumption rates of B30 downward toward the petroleum diesel threshold.

The engine performance in terms of brake specific fuel consumption (BSFC) across various fuel blends is depicted in Fig. 5. Typically, the higher kinematic viscosity of waste cooking oil (WCO) biodiesel deteriorates the spray and atomization characteristics inside the engine cylinder, subsequently increasing the BSFC. However, the addition of MgO nanoparticles (NPs) to the B30 blend counteracts this drawback. At full engine load, the baseline B30 blend exhibited a BSFC value of 0.28 kg/kW·h, which dropped to 0.241 kg/kW·h with the addition of 60 ppm MgO, representing a significant full-load reduction of 13.93%. Crucially, across the entire spectrum of engine operating loads, the introduction of MgO NPs at concentrations of 10, 30, and 60 ppm yielded cumulative average BSFC reductions of 5%, 10%, and 11%, respectively. This gradual improvement is attributed to the higher evaporation rate of the fuel droplets, enhanced fuel-air mixing, and the catalytic activity of the nano-doped blends. The high surface-area-to-volume ratio of the NPs promotes enhanced oxidation and improves overall combustion efficiency under varying thermal states [39].

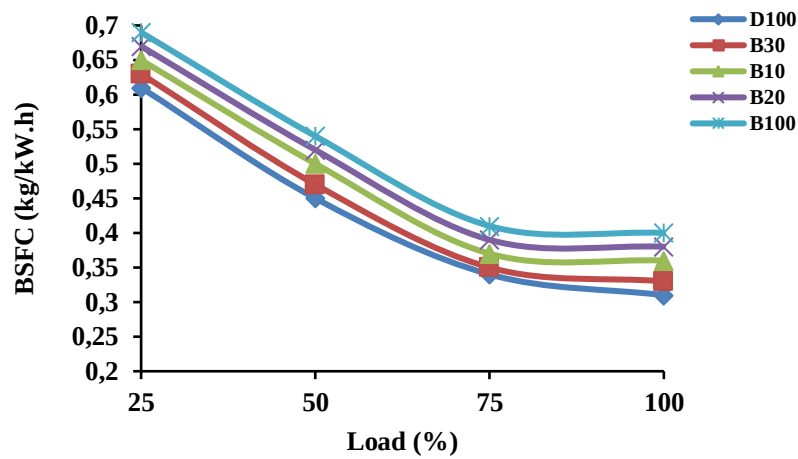


Fig. 4. Relationship between BSFC and engine load for diesel and WCO biodiesel blends

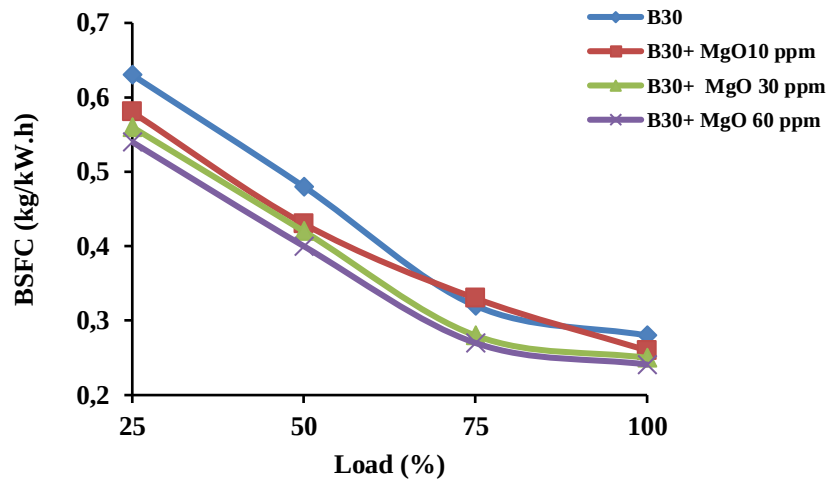


Fig. 5. Relationship between BSFC and engine load for biodiesel blends with MgO NPs

3.2 Brake Thermal Efficiency (BTE)

Brake thermal efficiency (BTE) refers to the efficiency with which an engine converts the chemical energy of fuel into useful mechanical energy. The high cetane number of biodiesels reduces the engine's ignition delay period [40]. Fig. 6 shows the brake thermal efficiency of diesel and biodiesel blends. For all tested fuels, BTE increases with increasing engine load. This behavior occurs because a higher fuel input at elevated loads enhances the combustion process and improves overall efficiency. The higher BTE of the B30 blend compared to B10 and B20, despite its higher viscosity and lower heating value, is explained by the fluid dynamics of the IDI pre-combustion chamber. During compression, air is forced through a narrow throat, creating intense micro-turbulence and swirl that breaks down the thick B30 droplets, overriding the viscosity penalty and ensuring

complete air-fuel mixing. While B100 fails because its excessive viscosity resists this shearing force, B30 strikes an ideal physicochemical balance, exhibiting better combustion efficiency than other blends [41]. Furthermore, when MgO nanoparticles are added to B30 at concentrations of 10, 30, and 60 ppm, the BTE increases further due to the additional oxygen availability, higher evaporation rate, and the larger surface-area-to-volume ratio of the nanoparticles [42].

Fig. 7 shows the effect of engine load on the BTE of biodiesel blends with MgO nanoparticles. The thermal efficiency of the B30 blend with 60 ppm MgO nanoparticles reached 26.72%. It is higher than that of the neat B30 blend (25.81%). Under full load conditions, the BTE of B30 blended with 10, 30, and 60 ppm MgO increased by 1.28%, 2.13%, and 3.52%, respectively.

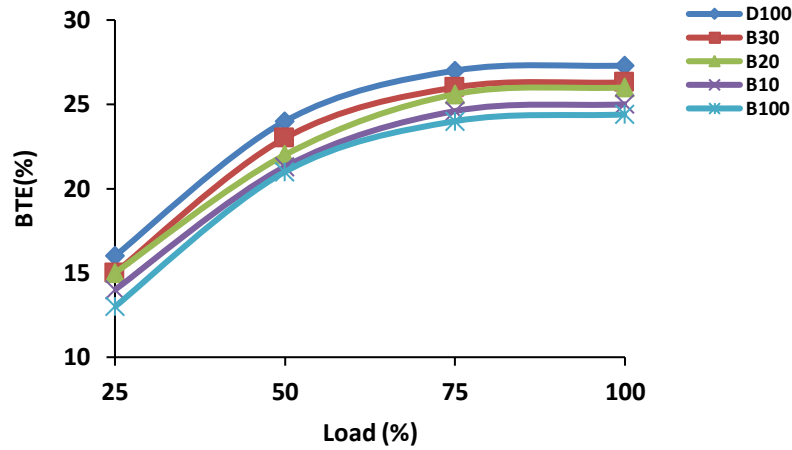


Fig. 6. Relationship between BTE and engine load for diesel and WCO biodiesel blends

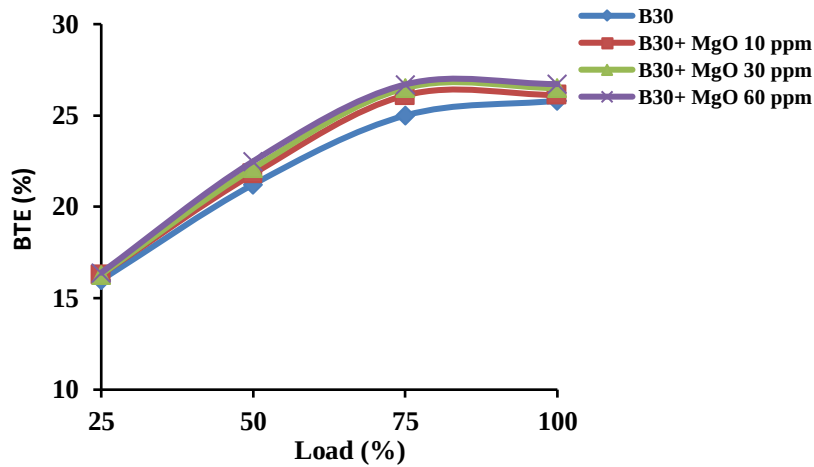


Fig. 7. Relationship between BTE and engine load for biodiesel blends with MgO NPs

3.3 Emission Analysis

Emission analysis is the practice of detecting and examining the gases and pollutants released by an engine while it is working. This is performed to assess the engine impact on the environment and to ensure the compliance with emission regulations and standards. The following contaminants are frequently evaluated in emission analysis.

3.3.1 Carbon Monoxide

Carbon monoxide (CO) is produced in the exhaust of rich-running engines because there is insufficient oxygen to convert all the carbon in the fuel into carbon dioxide. Compared to fossil fuels, biodiesel usually exhibits lower CO emissions. This is mainly attributed to its higher oxygen content, which accelerates the oxidation of CO. For all tested fuels, carbon monoxide (CO) emissions were higher at full load than at no load. When the engine operates at full load, an excessively rich

air-fuel mixture can lead to increased carbon monoxide emissions. The CO emissions of diesel and biodiesel blends are shown in Fig.8. Some of the carbon was released into the environment as carbon monoxide because not all of the carbon in the fuel was completely oxidized [43]. The lack of oxygen in the molecular structure of diesel fuel may be one of the causes of higher carbon monoxide emissions, as oxygen availability plays a critical role in combustion. Biodiesel emits less carbon monoxide than diesel. This trend continues as the biodiesel percentage in the blend increases. Fuels containing MgO nanoadditives show improved combustion owing to their higher effective oxygen availability.

The reduction in carbon monoxide emissions observed with the addition of MgO to the B30 blend at concentrations of 10, 30, and 60 ppm demonstrates the catalytic activity of the nanoparticles in biodiesel. MgO nanoparticles promote interfacial fuel processes, enhancing atomization, oxidation, and overall combustion efficiency [44]. The CO emissions of nanoparticle-doped biodiesel blends are illustrated in Fig.9. At full engine load, the baseline B30 blend exhibited a CO emission value of 0.21% vol., which significantly dropped to 0.152% vol. with the addition of 60 ppm MgO, representing a specific full-load reduction of 27.62%. Crucially, when analyzed across the entire spectrum of engine operating loads, the incorporation of MgO nanoparticles at concentrations of 10, 30, and 60 ppm yielded cumulative average CO reductions of approximately 10%, 15%, and 30%, respectively. This broader emission mitigation highlights the stable catalytic oxidation capability of the nanoadditives under varying load conditions. The addition of nano-magnesium oxide (MgO) to fuel significantly lowers carbon monoxide emissions by improving combustion efficiency.

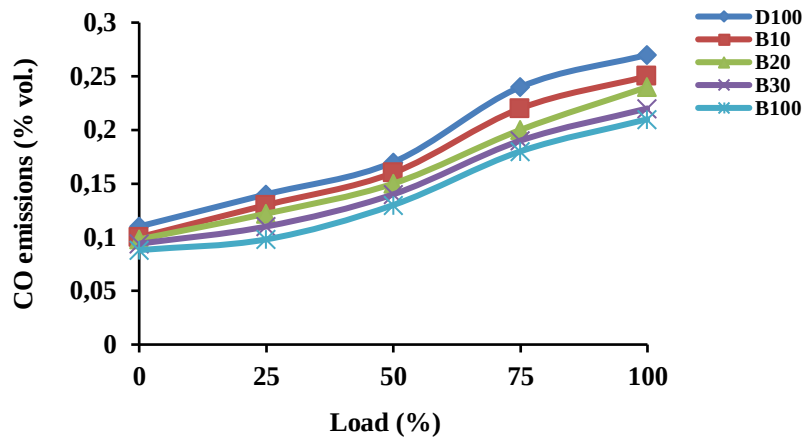


Fig. 8. Relationship between CO percentage and engine load for diesel and WCO biodiesel blends

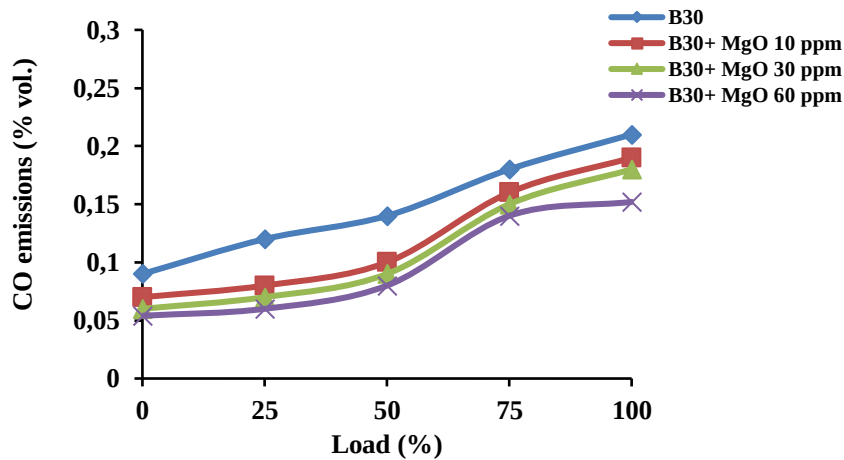


Fig. 9. Relationship between CO percentage and engine load for WCO biodiesel with MgO NPs fuel blends

Due to their large surface area and catalytic properties, MgO nanoparticles promote more complete oxidation of hydrocarbon molecules and facilitate the conversion of CO to CO₂. MgO nanoadditives also enhance fuel atomization and reduce ignition delay, improving fuel-air mixing and reducing incomplete combustion products.

3.3.2 Hydrocarbon (HC) Emission

For all fuel samples under study, HC emissions generally varied with changing engine load conditions at the constant operating speed of 1500 rpm. Biodiesel generally produces lower HC emissions due to its higher oxygen content, which promotes faster and more complete combustion. Fig.10 presents the HC emissions of diesel and biodiesel blends. Increasing the biodiesel percentage in the blend significantly reduces HC emissions compared to diesel fuel [45].

Most studies report a reduction in HC emissions when MgO nanoparticles are added to any biodiesel blends. An oxygen-donating catalyst is required to promote complete oxidation reactions, and MgO fulfills this role effectively. These improvements are primarily due to enhanced combustion processes within the combustion chamber [46]. Hydrocarbon emissions decreased with the addition of magnesium oxide nanoparticles to the B30 blend at concentrations of 10, 30, and 60 ppm. This reduction is attributed to the catalytic activity of MgO nanoparticles, which enhance the fuel-air interface and improve combustion efficiency. The HC emissions of MgO nanoparticle-doped biodiesel blends are shown in Fig.11. Compared to the B30 blend, which exhibited HC emissions of 68 ppm, the addition of 60 ppm MgO reduced HC emissions to 50 ppm. The incorporation of MgO nanoparticles at concentrations of 10, 30, and 60 ppm resulted in HC emission reductions of 18%, 22%, and 26%, respectively.

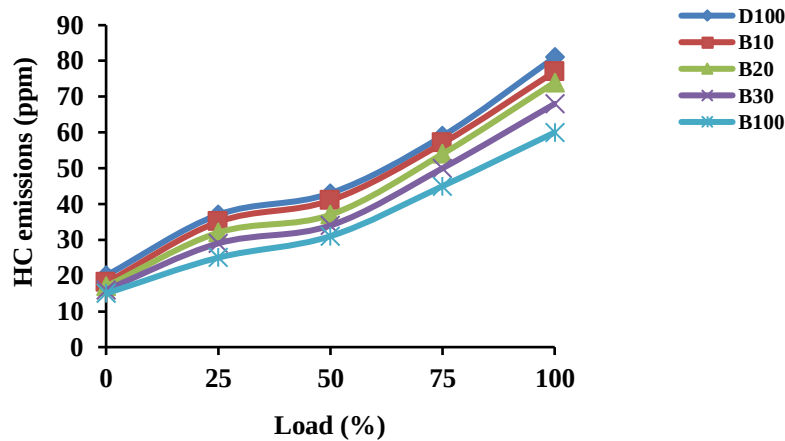


Fig. 10. Relationship between HC emissions and engine load for diesel and WCO biodiesel blends

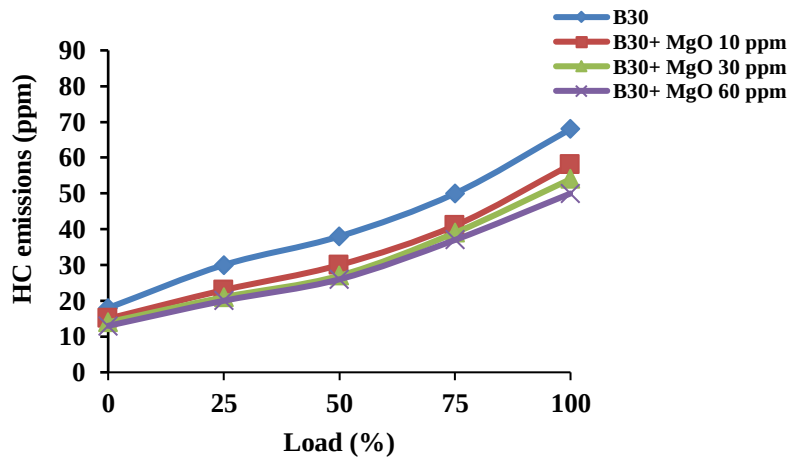


Fig. 11. Relationship between HC emissions and engine load for WCO biodiesel with MgO NPs fuel blends

3.3.3 Nitrogen Oxides (NO_x) Emissions

Nitrogen oxides (NO_x) are among the major emissions from diesel engines and are primarily formed through thermal mechanisms owing to high combustion temperatures and excess oxygen availability. For all tested fuels, NO_x emissions increased with increasing engine load. At full load, the primary cause of elevated NO_x emissions is the higher combustion temperature. Biodiesel blends exhibit in general NO_x emissions comparable to or slightly higher than diesel fuel. This increase is mainly attributed to the inherent oxygen content of biodiesel, which promotes higher combustion temperatures. As engine load increases, the rapid rise in combustion temperature leads to increased NO_x formation [47]. The NO_x emissions of diesel and biodiesel blends are shown in Fig. 12.

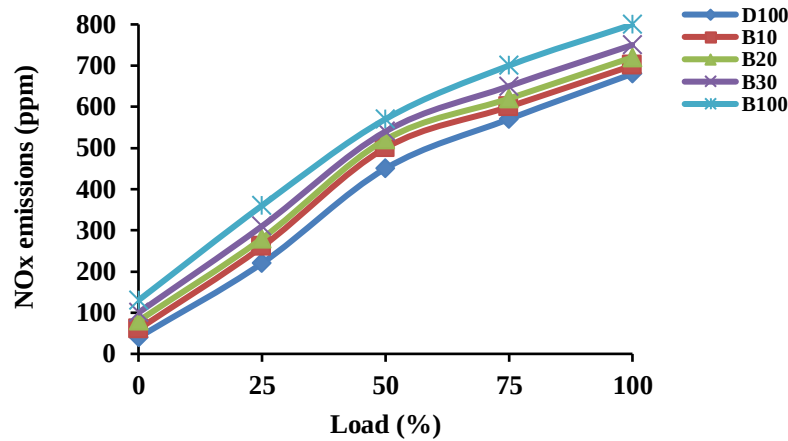


Fig. 12. Relationship between NO_x emissions and engine load for diesel and WCO biodiesel blends

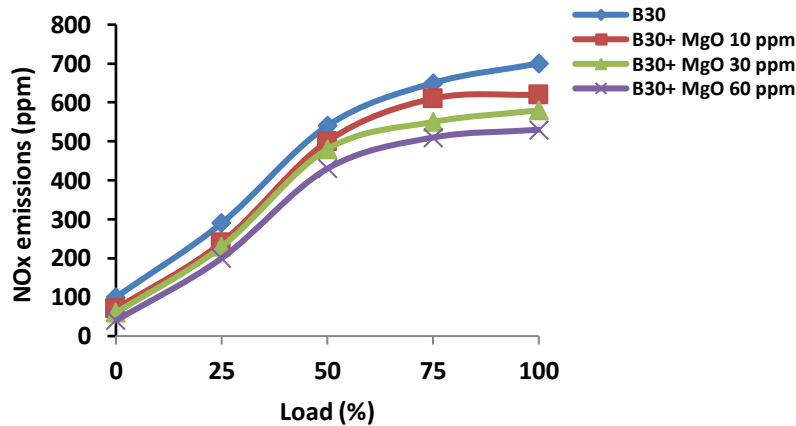


Fig. 13. Relationship between NO_x emissions and engine load for WCO biodiesel with MgO NPs fuel blends

The addition of MgO nanoparticles can enhance oxidation reactions and reduce nitrogen oxide emissions due to their catalytic influence during combustion [22]. Fig.13 shows the (NO_x) emissions of MgO nanoparticle-doped biodiesel blends. Quantitatively, at maximum engine load, the baseline B30 blend exhibited a peak (NO_x) concentration of 700 ppm, whereas the introduction of 10, 30, and 60 ppm MgO progressively minimized these emissions, with the 60ppm dosage lowering the concentration to 530 ppm, thereby demonstrating a 24.3% reduction. The simultaneous increase in BTE and reduction in (NO_x) emissions with nano-MgO addition is explained by the alteration of the combustion phases, which affects heat transfer characteristics without a simplistic drop in bulk temperature. The shorter ignition delay reduces fuel accumulation during the delay period, effectively suppressing the intense premixed combustion phase and preventing localized peak temperature spikes responsible for thermal (NO_x) formation.

Conversely, when MgO nanoparticles were added to the B30 blend, (NO_x) emissions decreased due to improve in-cylinder thermal conductivity and controlled diffusion combustion temperatures. This exceptional thermal conductivity effectively homogenizes localized high-temperature zones (hotspots) within the combustion chamber, thereby suppressing the thermal (NO_x) formation mechanism governed by the extended Zeldovich mechanism. During this subsequent diffusion phase, the catalytic oxygen-donating capability of the nano-MgO particles accelerates oxidation and ensures complete fuel conversion, enhancing thermal efficiency without generating the destructive temperature spikes that dictate NO_x generation.

3.3.4 Smoke Emissions

As the engine load intensified, a corresponding elevation in smoke opacity was documented across all evaluated fuel configurations. This upward trajectory is primarily driven by the escalated fuel injection rates required to sustain higher load thresholds, which inevitably induces localized fuel-rich pockets within the combustion chamber and restricts the oxygen available for complete chemical conversion. Moreover, the elevated thermal states inside the cylinder accelerate soot nucleation reactions, promoting the generation of carbonaceous particulates. Nonetheless, the biodiesel configurations systematically yielded lower smoke emissions than conventional diesel fuel throughout the operational spectrum. The presence of chemically bound molecular oxygen within the biodiesel matrix enhances the post-oxidation of soot precursors and elevates overall combustion efficiency [48, 49]. The experimental variations in smoke opacity for the baseline diesel and WCO biodiesel blends under different operating loads are illustrated via a continuous line chart in Fig. 14. Crucially, the incorporation of synthesized MgO nanoparticles drove an incremental suppression in smoke opacity by elevating thermal efficiency.

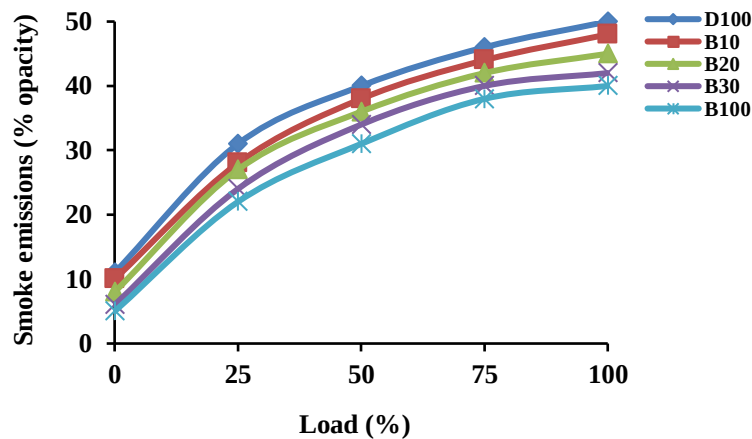


Fig. 14. Relationship between smoke emissions and engine load for diesel and WCO biodiesel blends

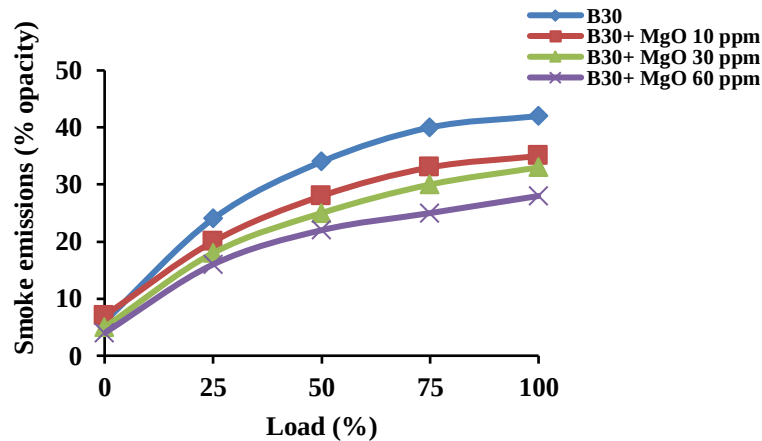


Fig. 15. Relationship between smoke emissions and engine load for WCO biodiesel with MgO NPs fuel blends

These metal-oxide nanoadditives function as effective combustion-promoting catalysts, facilitating rapid oxidation pathways and ensuring a more uniform thermal distribution within the cylinder. Consequently, elevating the MgO dosage from 10 to 60 ppm systematically lowered the smoke emission curves. The fuel mixture modified with 60 ppm MgO demonstrated the lowest smoke opacity levels among all nanoparticle-treated formulations. Furthermore, Fig. 15 displays these smoke opacity levels (%) as a function of engine load across various nanoparticle concentrations using a standardized continuous line chart, verifying the robust capability of MgO additives in mitigating exhaust smoke emissions from compression-ignition engines. Quantitatively, at 100% engine load, the baseline B30 blend exhibited a smoke opacity of 42%, which was progressively reduced to 35%, 33%, and 28% with the addition of 10, 30, and 60 ppm MgO, respectively, representing a maximum reduction of 33.3% at the highest nanoadditive dosage.

3.4 Circular Economy and Nanoadditives (MgO) in Biodiesel

A circular economy aims to eliminate waste and promote the ongoing use of resources while rebuilding natural systems. This approach contrasts sharply with the traditional linear economy model of “take, make, and dispose”. Applying circular economy principles to biodiesel production using MgO nanoparticles requires several complementary strategies. The use of waste cooking oil represents an important step in designing out waste and pollution since it is a byproduct whose utilization directly reduces waste generation. Furthermore, MgO nanoparticles are employed to improve combustion efficiency and reduce emissions of harmful gases such as CO and NO_x [50-54].

In addition, advocating for the use of sustainable waste oils with positive environmental impacts is important. Biodegradable byproducts of biodiesel production, such as glycerol, can be valorized by conversion into biogas for energy generation or used as a feedstock in chemical and industrial applications. These measures jointly reduce waste and support the regeneration of natural systems. The addition of MgO nanoparticles not only enhances combustion efficiency but also lowers hazardous emissions such as CO and NO_x [46], and thereby improving overall environmental sustainability. Moreover, MgO NPs can be restored from industrial wastes. These include steel mill slag, which reduces reliance on virgin raw materials and mitigates industrial waste streams [55]. Studies have shown that the lubricating properties of biodiesel blended with nanoadditives can reduce engine wear as well as extend the service life of engine components [56, 57]. Ensuring sustainability therefore involves integrating circular economy practices such as resource recovery, recycling, and waste minimization.

By enabling biodiesel production within a closed-loop framework, this approach minimizes environmental impacts and improves resource efficiency throughout the biodiesel life cycle [58]. Compared with cerium oxide, magnesium oxide can be produced more easily and sustainably [59]. Zinc oxide is another studied nanoadditive, which has been found able to improve engine performance and reduces emissions as well. However, its more complicated processing requirements make MgO NPs a more attractive option for biodiesel applications. Overall, while both additives contribute to sustainability, magnesium oxide offers advantages in production efficiency, cost-effectiveness, and environmental compatibility. While the integration of MgO nanoadditives offers clear thermodynamic benefits, completing a holistic sustainability analysis necessitates addressing the environmental and health implications of airborne particulate emissions. During the high-temperature combustion phase, synthesized metal-oxide nanoparticles undergo rapid thermal excitation and are partially emitted within the exhaust stream. Sub-micron and nano-sized MgO particles released into the atmosphere pose potential nanotoxicity risks, as their minimal scale allows deep respiratory penetration and cellular translocation in biological systems. The integration of waste cooking oil (WCO) conversion and magnesium oxide (MgO) nanocatalysis provides a tangible empirical model that aligns perfectly with the circular economy tenets established by the Ellen MacArthur Foundation, which focus on eliminating waste, circulating products, and regenerating natural systems. Mechanistically, achieving a high transesterification yield of 88% effectively demonstrates the technical feasibility of keeping organic waste materials in continuous productive circulation rather than allowing them to degrade environmental sinks. To mitigate these risks and support absolute ecological friendliness, utilizing advanced after-treatment systems, such as commercial diesel particulate filters (DPFs), is essential

to trap ultrafine metallic fractions. Furthermore, because MgO safely transforms into magnesium carbonates when interacting with ambient CO₂ and moisture over time, its long-term environmental accumulation risks are significantly lower than those of transition or heavy metal oxide counterparts. To further demonstrate the commercial viability of the proposed method under the circular economy framework, a quantitative cost-benefit analysis was correlated with the engine performance. The cumulative additional expenses encompass the raw precursor acquisition for chemical MgO synthesis, electricity consumption during the high-shear ultrasonication stability phase 0.12\$/L, and processing overheads, totaling approximately 0.45\$ per liter of optimized nano-doped biodiesel. Conversely, the documented peak reduction in specific fuel consumption 13.93% lower (BSFC) at full load translates directly into a net fuel saving of approximately 0.18\$ per operating hour under steady-state configurations. Considering continuous institutional or industrial power generation profiles, the initial processing expenditure achieves a calculated economic break-even threshold within approximately 180 to 220 operational hours. This concrete financial balance validates that the thermal efficiency gains and fuel-saving capabilities decisively outweigh the nanomaterial preparation overheads, proving the robust economic feasibility of the proposed technique.

3.5 Artificial Neural Network (ANN) Performance

The final multi-output ANN model, which was trained using Bayesian regularization (trainbr), demonstrated strong and consistent predictive capability across all six-engine performance and emission outputs. The selected network architecture, two hidden layers with 18 and 12 neurons, provided an effective balance between learning capacity and generalization, as reflected in the test-set performance metrics. The model achieved an average coefficient of determination (R^2) of 0.9439 on the test dataset across all outputs. The individual RMSE and MAE values were evaluated separately for each output in their respective physical units. The relatively small difference in performance between training and testing ($\Delta R^2 \approx -0.0192$) indicates that overfitting was successfully controlled, and confirms the robustness of the Bayesian regularization strategy. A more detailed examination of individual outputs reveals varying degrees of prediction accuracy. It reflects the intrinsic complexity and noise sensitivity of each response variable. Brake thermal efficiency (BTE) was predicted with the highest accuracy. An R^2 of 0.9981 was achieved on the test set and a low RMSE of 0.4658%. In a similar way, specific fuel consumption (SFC) showed strong predictive agreement, with a test R^2 of 0.9599 and an RMSE of 0.03386 kg/kW·hr. These results indicate that the ANN captured the dominant thermodynamic trends governing engine efficiency with high reliability. Emission-related outputs exhibited slightly lower, yet still satisfactory, predictive performance. Hydrocarbon (HC) and nitrogen oxides (NO_x) emissions were predicted with test R^2 values of 0.9526 and 0.9573, respectively. While the absolute error metrics of them were higher, and in particular for NO_x due to its wider numerical range, the relative agreement remains strong, indicating the highly nonlinear formation mechanisms involved. Smoke opacity was predicted with a test R^2 of 0.9383 and reflected the model's ability to track particulate-related trends across varying fuel blends and operating loads. Carbon monoxide (CO) showed the lowest test-set performance ($R^2 = 0.8571$). This reduction is consistent with the known sensitivity of CO formation to small fluctuations in combustion conditions and measurement uncertainty. Even so, the model successfully captured the overall trend and values of CO emissions, as evidenced by the low absolute RMSE (0.0231% vol.). Table 7 presents the test-set prediction performance for each output parameter, including R^2 , RMSE, and MAE in their respective physical units.

Table 7. Test-set prediction performance of the developed multi-output ANN model

Output parameter	Test R^2	RMSE	MAE
SFC (kg/kW·hr)	0.9599	0.033862	0.023408
BTE (%)	0.9981	0.465815	0.395315
CO (% vol.)	0.8571	0.023125	0.021307
HC (ppm)	0.9526	4.812485	3.943458
NO _x (ppm)	0.9573	47.549845	39.095067
Smoke (% opacity)	0.9383	3.822480	3.104034

The test-set R^2 values reported above were calculated exclusively from the eight independent test samples. In contrast, the R^2 values displayed in Fig. 16, which presents parity plots comparing ANN-predicted values against experimental measurements for all six outputs were calculated using all 40 experimental and ANN-predicted observations. Therefore, these values represent the overall agreement of the model across the complete dataset. In all cases, the majority of data points, both training and testing, cluster closely around the ideal $y = x$ line.

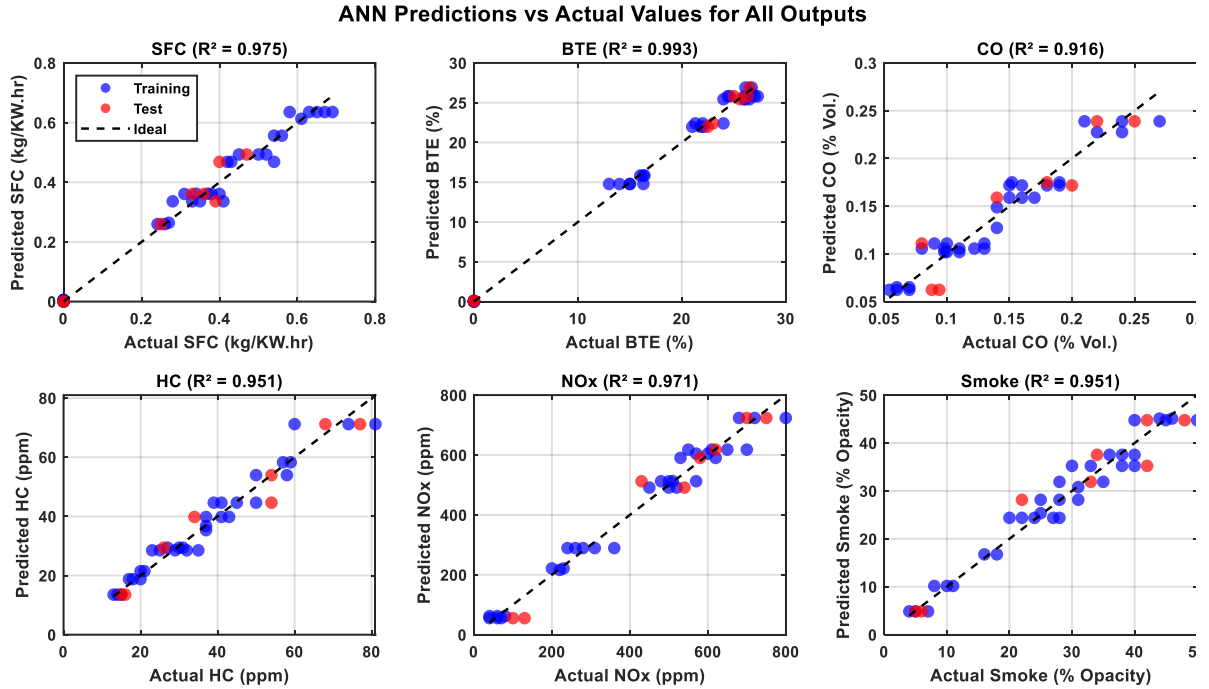


Fig. 16. Parity plots comparing experimental and ANN-predicted values for all six-engine performance and emission outputs. The R^2 values shown in the plots were calculated using all 40 observations

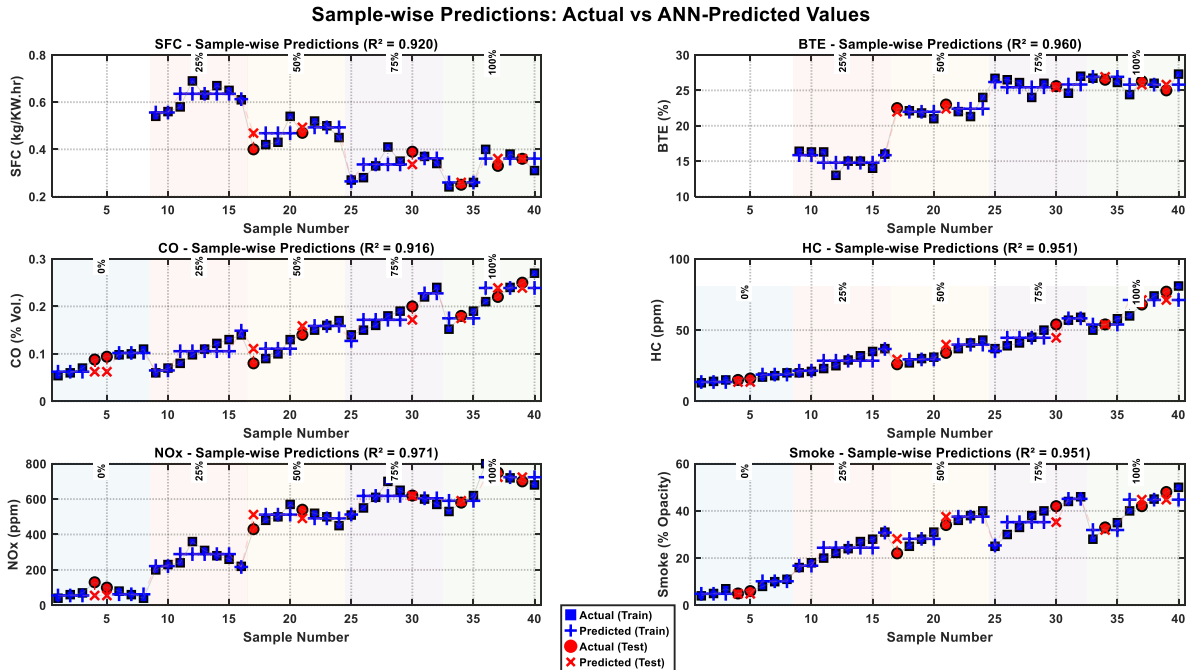


Fig. 17. Sample-wise comparison of experimental and ANN-predicted values across different fuel blends and operating conditions for all output parameters. The R^2 values shown were calculated from the plotted observations and do not represent the independent test-set R^2 values

This tight alignment confirms the high prediction accuracy obtained numerically. It also demonstrates the absence of systematic overprediction or underprediction. Notably, the densest clustering is observed for BTE and SFC, whereas slightly larger scatter appears for emission parameters and especially for CO and smoke opacity. Even so, deviations remain bounded and randomly distributed, suggesting that prediction errors arise primarily from process variability rather than structural model bias. To further assess model generalization, sample-wise comparisons between experimental and predicted values are illustrated in Fig. 17. Across different fuel blends and load conditions, the ANN regularly tracks the experimental trends for all outputs. The R^2 values associated with Fig.17 were calculated from the experimental and ANN-predicted values displayed in the sample-wise plots and therefore include the plotted training and test observations rather than the independent test set alone. Transitions between operating regimes are well captured. This indicates that the model has internalized the underlying response behavior rather than memorizing individual data points. In some test samples, there are noticeable differences, particularly for emission outputs at higher loads. These differences highlight the inherent difficulty of predicting emissions governed by coupled chemical kinetics and transient combustion phenomena. Importantly, however, the overall trend fidelity remains intact, and the deviations do not compromise the model's predictive usefulness. The difference between training and testing performance across all outputs remains modest, with ΔR^2 values ranging from -0.0741 (CO) to $+0.0064$ (BTE), based on the corresponding training and independent test-set R^2 values. This relatively small difference confirms that the ANN maintains strong generalization capability despite the limited dataset size and multi-output complexity. The consistency between numerical metrics and graphical diagnostics demonstrates that the developed ANN functions not merely as a statistical fitting tool, but as a reliable digital surrogate of the experimental engine system. Within the studied operating range, the model can therefore be confidently employed for performance prediction, comparative fuel evaluation, and preliminary optimization studies, reducing the need for extensive experimental campaigns.

4. Conclusions

In this experimental and numerical study, waste cooking oil biodiesel was synthesized via the transesterification of waste cooking oil and subsequently blended with petroleum diesel. Magnesium oxide (MgO) nanoparticles were added to the biodiesel blends at concentrations of 10, 30, and 60 ppm. From the results of this study, the following conclusions can be drawn:

- The measured physicochemical properties of the produced biodiesel and MgO-doped blends were found to be within the permissible limits specified by ASTM standards.
- Compared with conventional diesel fuel, MgO nanoparticle-enhanced biodiesel demonstrated improved engine performance; specifically, as the concentration of MgO nanoparticles increased, brake-specific fuel consumption (BSFC) decreased by up to 11%.
- Brake thermal efficiency (BTE) increased by approximately 3.52% for the B30 blended with 60 ppm MgO.
- Significant reductions in exhaust emissions were observed. Carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx), and smoke opacity were all reduced by up to 30%, 26%, 24.3%, and 33.3%, respectively, compared to the base B30 blend.
- The developed multi-output artificial neural network (ANN), based on Bayesian regularization with an [18, 12] hidden-layer architecture, demonstrated high predictive accuracy for the six-engine performance and emission parameters. The model achieved an average test-set coefficient of determination (R^2) of 0.9439, with individual R^2 values ranging from 0.8571 for CO to 0.9981 for BTE. These results confirm the capability of the ANN to reliably predict engine performance and emission characteristics under the investigated fuel and operating conditions.

Although the incorporation of nanoparticles increases the initial fuel preparation cost, the long-term economic and environmental benefits stemming from improved combustion efficiency, reduced fuel consumption, lower emissions, and extended engine component life can outweigh these additional costs. The results of this study indicate that MgO nanoparticles are promising as well as effective fuel additives for biodiesel applications. It offers a viable pathway for partial

replacement of conventional diesel fuel in compression ignition engines. The findings support both industrial implementation and governmental policies. They have a goal to adopt cleaner and more sustainable fuel alternatives. However, the present study is limited by the use of a two-cylinder diesel engine, which may not fully represent real-world operating conditions. Therefore, future work should focus on multi-cylinder engines. Furthermore, future investigations should address the long-term colloidal stability, shelf-life, and potential sedimentation issues of MgO nanoparticles in biodiesel blends under various storage temperature. Also, it should perform long-duration testing to assess engine wear, durability, and long-term performance. This will provide an excellent evaluation of the commercial viability of MgO nanoparticle-enhanced biodiesel fuels. Overall, the B10, B20, and B30 waste cooking oil biodiesel blends showed compatibility with existing diesel engines without mechanical modifications, while the integration of MgO nanoparticles was essential to consistently lower NO_x emissions below those of petroleum diesel. These results further confirm the capability of waste cooking oil biodiesel, and in particular when enhanced with MgO nanoparticles, as a sustainable and environmentally friendly alternative fuel.

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