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Enhancing diesel engine performance and emissions with $\text{CaO} \cdot \text{Al}_2\text{O}_3$ -doped *Garcinia* biodiesel blends using a hybrid statistical-AI framework

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Abstract

The growing demand for sustainable energy and stringent emission regulations necessitate the development of cleaner alternative fuels for diesel engines. This study investigates the performance and emission characteristics of a binary biodiesel blend derived from *Garcinia gummi-gutta* (GGG) and *Garcinia indica* (GI) doped with $\text{CaO} \cdot \text{Al}_2\text{O}_3$ nanoparticles (NPs) in a compression-ignition engine. Biodiesel is produced via microwave-assisted transesterification, with a yield of 98.9%, and is characterized according to ASTM standards. A Central Composite Design (CCD) is employed to examine the effects of blend ratio (10–30%), nanoparticle concentration (60–180 ppm), compression ratio (14–18), and engine load (40–100%) on brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), and emissions (CO, UHC, and NOx). A hybrid multi-response optimization framework integrating the Desirability Function Approach (DFA), the Grey Wolf Optimizer (GWO), and the Starfish Optimization Algorithm (SFOA) is implemented to determine optimal engine conditions. Results indicate that nanoparticle doping enhances combustion efficiency by improving catalytic activity and oxygen availability. The optimal single-objective conditions yield a maximum BTE of 34.8%, minimum BSFC of 0.172 kg/kW·h, and reduced emissions (CO: 0.031 vol.%, UHC: 13.82 ppm, NOx: 92 ppm). Multiobjective optimization yields a composite desirability value of 0.938, and experimental validation confirms its predictive accuracy, with an average absolute deviation of 5.85%. The addition of $\text{CaO} \cdot \text{Al}_2\text{O}_3$ NPs increases the BTE by 11.86% and reduce BSFC, CO, and UHC by 1.72%, 38.89%, and 26.80%, respectively. However, NOx emissions increase slightly by 7.49%, attributed to improved combustion behaviour resulting from higher oxygen content, air–fuel ratio, and calorific value. The study demonstrates that GGG-GI biodiesel blends doped with $\text{CaO} \cdot \text{Al}_2\text{O}_3$ nanoparticles, combined with a hybrid statistical-AI optimization framework, offer a viable pathway to enhance diesel engine efficiency and reduce emissions, supporting sustainable biofuel deployment.

Keywords GGG + GI biodiesel, $\text{CaO} \cdot \text{Al}_2\text{O}_3$ NPs, Starfish optimization algorithm, DFA, CCD Performance, And emission characteristics

Introduction

Energy plays an important role in industrial development, transportation, and economic growth. Continuous population growth and rapid industrialization have significantly increased global energy demand over the past few decades [1]. Despite advancements in renewable technologies, fossil fuels, including coal, oil, and natural gas, still dominate the global energy portfolio, accounting for more than 80% of primary energy consumption [2]. The extensive use of fossil fuels has led to increased greenhouse gas (GHG) emissions, environmental degradation, and health concerns related to air pollution [3].

The transportation sector is one of the major consumers of petroleum fuels, accounting for more than 57% of global oil usage. Fossil fuel combustion contributes to global warming, fuel price instability, and energy security challenges [4]. Currently, non-renewable fossil sources supply approximately 84% of the world's total energy demand [5]. These factors highlight the need to develop alternative fuels that are technically viable, economically feasible, and environmentally sustainable [6].

Renewable energy resources such as hydro, wind, solar, geothermal, and biomass are considered promising alternatives [7]. Among these, biomass-based fuels offer advantages in terms of availability, carbon neutrality potential, and compatibility with existing engine infrastructure. Renewable sources contribute nearly 14% of global energy supply, with biomass accounting for a substantial share [8]. Biomass refers to organic raw material of biological origin, while biofuels are processed energy carriers derived from biomass [9, 10]. Biodiesel, produced through transesterification of vegetable oils or animal fats, has emerged as a suitable replacement for conventional diesel due to its biodegradability, lower sulphur content, and favourable combustion characteristics [11]. In addition, biodiesel enhances energy security through localized production and reduced dependence on imported petroleum [9].

The economic feasibility of biodiesel production is largely influenced by feedstock cost, which accounts for approximately 70–95% of total production expenses [7]. Therefore, selecting sustainable, cost-effective feedstocks is critical [7, 12]. To avoid food-versus-fuel conflicts and ensure environmental sustainability, non-edible oil-bearing species cultivated on marginal lands are increasingly investigated [13]. In this context, *Garcinia gummi-gutta* (GGG) and *Garcinia indica* (GI) are promising candidates due to their high oil content and non-food nature [14, 15]. GGG seeds contain approximately 30–40% oil and are widely available in southern India [15], while GI seeds contain around 23–26% oil and possess bioactive components of industrial relevance [14, 15]. Table 1 presents the summary details of single-oily feedstocks (SOFs) and multi-oily feedstocks (MOFs) derived biodiesel, and their performance and emissions when fuelled in diesel engines. Note that MOFs pose potential advantages such as a) increasing feedstock availability for continuous biodiesel production [16], reducing logistic cost and price fluctuations [16, 17], supporting revenue to farmers and the circular economy [16, 18], and customized fuel properties for improved combustion and emission reductions [19, 20]. Table 1 presents the summary results of different nanoadditives (MgO, ZnO, CeO, Fe₂O₃, TiO₂, Al₂O₃, Fe₃O₄, BaTiO₃, CuO, GO), experimental methods (FFD, CCRD, CCD, RSM, Taguchi, OFAT), and optimization methods (DFA, MEREC, MARCOS, ML, ANN, GRA, DTBO, EBOA, GWO) applied, resulting in enhanced engine performance and emission reductions fuelled with biodiesel blends. The use of nanoadditives (aluminium oxide and titanium dioxide) in biodiesel blends shows significant reductions

Table 1 Summary results of different feedstocks driven biodiesel, NPs, and their performance and emissions in diesel engines

Feedstock	NPs	Engine Variables	Performance & Emission	Methods employed	Major results	Ref
WCO	MgO	BB, ES, EL, NPC	BSFC, BTE	FFD	NPs in biodiesel blends ↑ BTE	[48]
WCO	ZnO	BB, NPC, EGR, CR	BTE, BSEC, CO, HC, NOx, SO	CCRD and DFA	DFA derives the highest D_o value of 88.53%, resulting in enhanced performance and emission responses	[49]
WHOB	CeO	NPC, CR, EL, HC, IP	NOx, UHC, VL, BSFC, BTE	CCRD	DFA-derived optimal conditions result in improved performance, reduced emissions, and reduced vibration	[50]
Jojoba	Fe ₂ O ₃	EL, NPC	BSFC, BTE, CO, CO ₂ , HC, Nox	RSM and DFA	DFA with a D_o value of 74.59% results in improved performance and reduced emission responses	[37]
Manilkara zapota	TiO ₂	EL, NPC, CR, IP, IT	BTE, BSFC, HC, CO, NOx	CCD and GA	GA determined that optimal conditions result in enhanced performance and emission responses	[51]
WCO	CeO	EL, NPC, IP, BB	CO, VL, BSFC, BTE	Taguchi, MEREC, MARCOS	NPC poses the highest influence, followed by EL, IP, and BB	[32]
Neem	Al ₂ O ₃	EL, NPC, biodiesel, diesel	BTE, BSFC, CO ₂ , NOx, HC	OFAT & ML	NPC improves the combustion and reduces emission characteristics in biodiesel blends	[52]
Tobacco	CeO	BB, EL	BTE, BSFC, CO, HC, NOx, SO	ANN and DFA	BB (20%) and CeO ₂ NPC result in improved performance and emission responses	[53]
Spirulina microalgae	Fe ₃ O ₄	EL, NPC, CR	BTE, BSFC, CO, CO ₂ , HC, NOx	RSM and DFA	DFA produces the highest D_o value of 82.99% results in improved performance and emission responses	[54]
Spirulina microalgae	BaTiO ₃	NPC, EL	BTE, BSFC, CO, CO ₂ , HC, NOx, SO	CCD and DFA	DFA results in the highest D_o value of 74.49%, leading to improved performance and emission responses	[35]
Mahua	ZnO	EGR, IT	HRR, CP, BTE, BSEC, CO, HC, SO, NOx	RSM and ANN	RSM predictions are comparatively better than ANN	[55]
Microalgae	Fe ₃ O ₄	BB, EL	EGT, BTE, BSFC, CO, HC, SO, NOx	CCD, ML, and DFA	DFA produces the highest D_o value of 91.0%, resulting in improved BTE, BSFC, and NOx performances	[56]
Jojoba	CuO	BP	BTE, EGT, CO ₂ , CO, HC, smoke, NOx	OFAT	CuO reduces ignition delay by improving chemical reaction rates	[57]
Sesame oil	GO	NPC, EL	BP, BSFC, EGT, CO, HC, NOx	RSM	GO has a positive effect on performance and emissions	[58]
Waste coconut + fish oils	MgO	BB, NPC, ES, EL	BTE, BSFC, HC, CO, NOx	CCD, GRA, GWO, DTBO, and EBOA	MgO NPs improve engine performance and reduce emissions	[36]

Al₂O₃ aluminium oxide, ANN artificial neural networks, BaTiO₃ barium titanate, BB biodiesel blends, BSFC brake specific fuel consumption, BSEC brake specific energy consumption, BTE brake thermal efficiency, CCD central composite design, CCRD central composite rotatable design, CeO cerium oxide, CO₂ carbon dioxide, CO carbon monoxide, CR compression ratio, CuO copper oxide, D_o overall desirability function value, DFA desirability function approach, DTBO driving training-based optimization, EBOA election-based optimization algorithm, EGR exhaust gas recirculation, EL engine load, ES engine speed, Fe₂O₃ iron oxide (hematite), Fe₃O₄ iron oxide (magnetite), FFD full factorial design, GA genetic algorithm, GRA grey relational analysis, GWO grey wolf optimizer, GO graphene oxide, HC hydrocarbon, IP injection pressure, IT injection timing, MARCOS measurement alternatives and ranking according to compromise solution, MEREC method based on the removal effects of criteria, MgO magnesium oxide, ML machine learning, NPC nanoparticle concentration, NPs nanoparticles, NOx nitrogen oxide, OFAT one factor at a time, RSM response surface methodology, SO smoke opacity, TiO₂ titanium dioxide, VL vibration level, WCO waste cooking oil, ZnO zinc oxide, WHOB Water Hyacinth oil biodiesel

in emissions and enhanced engine performance [21–23]. However, limited research has examined their combined utilization biodiesel blends with multiple oily feedstocks (GGG + GI) with mixed nanoadditives ($\text{CaO}.\text{Al}_2\text{O}_3$) in diesel engine applications.

Statistical design of experiments (DOE) methods, such as Taguchi methods, FFD, and RSM-driven CCD, CCRD, and BBD, are widely employed for biodiesel production and engine parameter optimization studies [24–26]. Table 1 presents details of the different experimental methods used to analyze engine performance and emission characteristics for various biodiesel feedstocks. The experimental methods (CCD, FFD, CCRD, Taguchi, BBD) allow the investigator to identify influencing factors, thereby enabling monitoring of engine performance and emission characteristics [26, 27]. DOE approaches possess significant advantages over OFAT methods are due to the following reasons such as: a) estimate the individual and interaction factor effects of all parameters simultaneously [28, 29], b) allow investigator significantly reduce time, cost, and experimental trials [28, 29], c) correlate input and output variables enable investigator to establish empirical regression equations that offers a reliable predictive tool [30, 31], d) simultaneous optimization of multiple conflicting outputs with the aid of experimental methods assisted with other optimization techniques (such as DFA, MEREC, TOPSIS, MARCOS and GRA) [32–37]. Although applying the Taguchi method significantly reduces experimental runs and determines optimal parameter levels, it poses significant limitations over RSM, such as: a) inability to quantify full quadratic (linear, quadratic, and interaction) factor effects on analyzed variables [38], b) fails to establish predictive regression equations that define the input relationship with response [38, 39]. Optimization tasks carried out by traditional methods (DFA, MEREC, TOPSIS, MARCOS, and GRA) transform multiple conflicting response functions into a single objective function as a preprocessing step. Traditional optimization tools use a deterministic search procedure (search in a single direction) and yield solutions that can result in local minima or maxima; these shortcomings can be overcome by employing a stochastic search method [36, 40]. Stochastic search methods employ candidate solutions (a population) that explore solutions in multiple directions at many spatial locations simultaneously in a continuous problem space and balance exploration and exploitation phases, helping algorithms derive global solutions [41, 42]. The above literature review confirms that applying RSM to estimate full quadratic factor effects and establish empirical equations that could help artificial intelligence-driven stochastic search methods derive global solutions for multiple outputs that conflict with one another.

Artificial intelligence (AI) tools are applied in biodiesel research to optimize fuel spray dynamics with different bowl geometries [43] and to predict performance and emission characteristics for known combinations of engine variables [27, 44]. Table 2 presents the details of different AI-based population-driven stochastic search optimization algorithms (ABC, GOA, GA, CS, PSO, ACKTR-DE, HHO, TLBO, ANN-GA, NSGA-II, GWO, DTBO, EBOA) that determined optimal conditions for various biodiesel feedstocks (WCO, DSO, GI, CSO, RSO, PPJ, waste coconut, and fish oil) that enhance the engine performances and emission reductions. The NSGA-II produces many optimal solutions (mutually compatible) for multiple conflicting outputs, while the TOPSIS method is used to recommend a single optimal solution. However, the solutions vary depending on the weights assigned to individual outputs. Expert suggestions and equal weighting methods are used to assign weights to individual responses, which might

Table 2 Summary of results of optimal conditions applied for performance and emission reductions

Biodiesel	Input variables	Output variables	Methods	Remarks	Ref
WCO	EL, ES, BB	BT, HC, BSFC, CO, NO _x	ABC	ABC determines that optimized conditions produced better performance and emission reduction	[59]
NR	BB, EL	BTE, BSFC, CO, NO _x , CO ₂ , HC, SO	GOA	GOA solves empirical equations and derives optimal engine performance and emission solutions	[60]
DSO	ES, BB	BP, BT, BSFC, CO, CO ₂ , HC, O ₂ , and NO _x	GA	GA determines that optimal conditions produced better engine responses	[61]
NR	ER, BB,	BSFC, BTE, CO, CO ₂ , HC, and NO _x	GOA	GOA solves regression equations and determines optimal conditions that produce better engine output	[62]
NR	ES, ET	PM, HC, CO, BSFC, CO ₂ , NO _x ,	CS, PSO	Two algorithms (CS and PSO) show identical optimal conditions, with CS being computationally efficient	[46]
NR	EL, ES, BB	BP, BT, BSFC, CO, smoke, and NO _x	GA	GA determines optimized conditions that result in better emission and performance responses	[63]
WCO	IP, ET, BB	BTE, BSFC, EGT, NO _x , HC, CO, Smoke	ACKTR-DE, HHO	HHO outperforms ACKTR-DE in optimizing the engine responses	[45]
WCO	BB, PG	BSFC, BTE, CO, CO ₂ , NO _x , SO ₂	RSM, ANN-GA-RSM	The ANN-GA-RSM outperforms RSM in deriving the optimal condition	[64]
GI	EL, IT, IP, BB	BSFC, BTE, CO, HC, NO _x	RSM, TLBO	TLBO determines that the optimal condition resulted in the highest D _o value of 0.9432, resulting in better engine responses	[65]
WCO	EL, BB	BP, BTE, BSFC, CO, HC, NO _x , smoke	TOPSIS, ANN	TOPSIS method determines that the optimal condition showed better engine performance and emission reductions	[34]
CSO	EL, BB, IT	BTE, BSFC, CO, HC, NO _x , CO ₂	NSGA-II, TOPSIS	NSGA-II determines multiple optimal solutions, and TOPSIS method chooses the single best optimal condition	[33]
RSO	CR, EL, BB, IP, SC	BTE, BSFC, CO, HC, NO _x	NSGA-II, RSM	NSGA-II determines that optimal conditions produced better engine performance and emission responses	[66]
PPJ	EL, CV, BB	BTE, BSFC, EGT, CO, CO ₂ , HC, NO _x , SO	PSO, DFA	PSO determines that optimal conditions result in improved engine performance and reduced emissions	[67]
Waste coconut + fish oils	BB, NPC, ES, EL	BTE, BSFC, HC, CO, NO _x	CCD, GRA, GWO, DTBO, EBOA	DTBO, EBOA, and GWO determine optimal conditions that improve engine performance and emission reductions	[36]

ABC artificial bee colony, ACKTR-DE Actor Critic with Kronecker-Factored Trust Region-Differential Evolution, ANN artificial neural network, CCD Central Composite Design, CS Cuckoo Search, CSO cotton seed oil, CV calorific value, DSO date seed oil, ET engine torque, GA genetic algorithm, GI Garcinia indica, GOA grasshopper optimization algorithm, HHO Harris Hawks Optimization, NR not reported, NSGA-II Non-dominated Sorting Genetic Algorithm II, PG propylene glycol, PPJ pumpkin and prosopis juliflora, PSO particle swarm optimization, RSO rubber seed oil, SC supercharging, SO smoke opacity, TLBO teaching-learning-based optimization, TOPSIS technique for order of preference by similarity to ideal solution

result in local solutions. The above shortcomings are addressed by conducting different case studies (equal weights, assigning maximum weights to one response, and maintaining minimum weights for the rest) and recommending the best solution based on the computed desirability value. Few researchers have compared the algorithm performances in determining optimal conditions, where HHO performs better than ACKTR-DE [45], CS is computationally more efficient than PSO [46], and EBOA requires less computation time than DTBO and GWO [36]. Recently introduced SFOA outperforms more than 95 algorithms in terms of solution accuracy and 97 algorithms in terms of

computational efficiency, validated against 65 benchmark functions [47]. The GWO algorithm is widely applied for biodiesel research [16, 31, 36, 39]. Note that no universally acceptable global optimization search methods have been defined in the literature yet. Therefore, comparing competitive GWO algorithms with recently introduced SFOAs is of practical relevance and demonstrates improved combustion and emission characteristics in diesel engines.

Despite extensive research, several limitations still remain unsolved. Most existing studies focus on single-response optimization, either maximizing performance or minimizing emissions independently, without addressing the inherent trade-offs (weights assigned to individual responses that involve conflicting objective functions). Diesel engine performance and emission characteristics are interrelated, and changes in operating conditions influence multiple outputs simultaneously. However, limited studies have systematically modelled these interdependencies. Furthermore, although statistical DoE techniques are well established, their integration with assigning weights and AI-based metaheuristic algorithms for multi-response optimization remains limited. In addition, while metal oxide nanoparticles have demonstrated potential to improve combustion efficiency and reduce emissions, limited investigations have evaluated $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles in biodiesel-diesel blends derived from novel non-edible feedstocks.

To address these gaps, the present study investigates a binary biodiesel blend derived from GGG and GI feedstocks for diesel engine applications. $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles are incorporated as combustion-enhancing additives to improve performance and emission characteristics. A hybrid optimization framework integrating CCD, DFA, weighting factors to responses, and the algorithms (GWO and SFOA) is developed to achieve multi-response optimization of engine operating parameters. Predictive mathematical models are established to capture relationships among performance and emission outputs, and AI-predicted optimal conditions are experimentally validated. This study provides an integrated experimental, statistical, and computational framework for evaluating novel non-edible binary (GGG + GI) biodiesel feedstocks. The proposed methodology improves engine performance and emission control while promoting sustainable fuel development for engineering applications.

Materials and methods

Experiments

Based on pilot experimental trials and expert consultations, the investigator identifies the most influential engine variables, namely engine load, nanoparticle concentration, compression ratio, and blend type, for the evaluation of engine performance and emission characteristics (Table 3).The comparative evaluation results for biodiesel blends show a negative influence on fuel properties (higher viscosity and density) beyond a biodiesel fraction of 10% (Table 4). These fuel properties negatively affect spray formation and combustion behaviour with increasing biodiesel fraction [35]. However, the above

Table 3 Control variables for GGG+GI biodiesel

Inputs	Notation	Levels
Blend type or biodiesel blend, vol. %	A or BT	10, 20, 30
Nanoparticle concentration	B or NPs	60, 120, 180
Compression ratio	C or CR	14, 16, 18
Engine load, %	D or EL	40, 70, 100

Table 4 Fuel properties of diesel, GGG + GI-derived biodiesel, and blend

Properties	ASTM standard	Diesel	B10	B20	B30	B100
Viscosity at 40 °C, mm ² /sec	D445	2.54	2.90	3.36	3.78	6.83
Density at 15 °C, kg/m ³	D4052	815	823	829	837	863
Flash point, °C	D93	54	67	85	94	187
Calorific value, MJ/kg	D240	43.82	43.22	42.51	42.06	41.22
Cetane Number	D613	46	47	48	49	57

B10: Biodiesel 10% + Diesel 90%; B20: Biodiesel 20% + Diesel 80%; B30: Biodiesel 30% + Diesel 70%;

negative benefits with higher biodiesel fractions (B20 and B30) are offset by lower emissions. Therefore, the operating levels of biodiesel blends (B10, B20, and B30) are determined based on pilot experimental trials and the literature [32, 36, 48, 49, 65–67]. The operating levels of nanoparticle concentration are selected based on literature reviews [35–37, 49, 52] and pilot experimental results. The NPC with lower dosages shows limited catalytic activity, whereas at higher dosages it promotes agglomeration and negatively affects fuel flow in the injector system [68]. During experimentation, beyond the critical value of 180 ppm of CaO·Al₂O₃ NPs, the engine performance and emissions do not show significant improvement. The operating levels of engine variables (CR and EL) are selected for experimentation based on literature and pilot experimental studies [36, 48, 49, 65]. During each experimental run, the operating engine speed is maintained at 1500 rpm.

Experiments on diesel engines and their components, using measuring devices, are presented in Fig. 1. Based on the experimental conditions, a hydraulic dynamometer is used to achieve the desired engine load. The engine is fueled with pure diesel (D100) and runs sufficiently for 30 min to attain steady-state conditions (i.e., achieving $\approx$ constant oil and water temperatures). The CaO·Al₂O₃ nanoparticles are dispersed in biodiesel-diesel blends (B10, B20, and B30) at concentrations ranging from 60 to 180 ppm using magnetic stirring for 30 min, followed by sonication at 40 kHz for 30 min. The ultrasonicator equipment (consisting of a sonicator and an ultrasonic bath) produces ultrasonic wave energy (thermal agitation) that enhances the mixing of CaO·Al₂O₃ NPs with biodiesel-diesel blends.

Furthermore, magnetic stirring with constant speed ensures homogeneous dispersion of nanoparticles in biodiesel blends. A similar procedure is adopted in previous studies reported in the literature [69]. To minimize the potential risk of agglomeration, sedimentation, and clogging in fuel injectors, smaller CaO·Al₂O₃ NPs (75.4 nm) are used. The prepared fuel is tested in a diesel engine within 15 min. Note that no visible phase separation or sedimentation is observed during the experimental investigation. To ensure consistent thermal and operational conditions across all biodiesel blends (B10, B20, and B30) with different NPC (60 to 180 ppm), the diesel engine is preconditioned or stabilized by fuelling neat diesel (D100) and running for 30 min prior to each experimental trial. The above procedure is repeated for each experimental condition according to the CCD matrix. The experimental runs are conducted with different sets of input variables (EL, NPs, CR, and BT) designed according to the central composite design matrices.

Testing the fuel properties

The hybrid oil (HO) derived from GGG and GI feedstocks enables biodiesel conversion via microwave-aided transesterification, yielding $98.9 \pm 0.42\%$. In this study, biodiesel blends are prepared with varying proportions of diesel and biodiesel to assess their

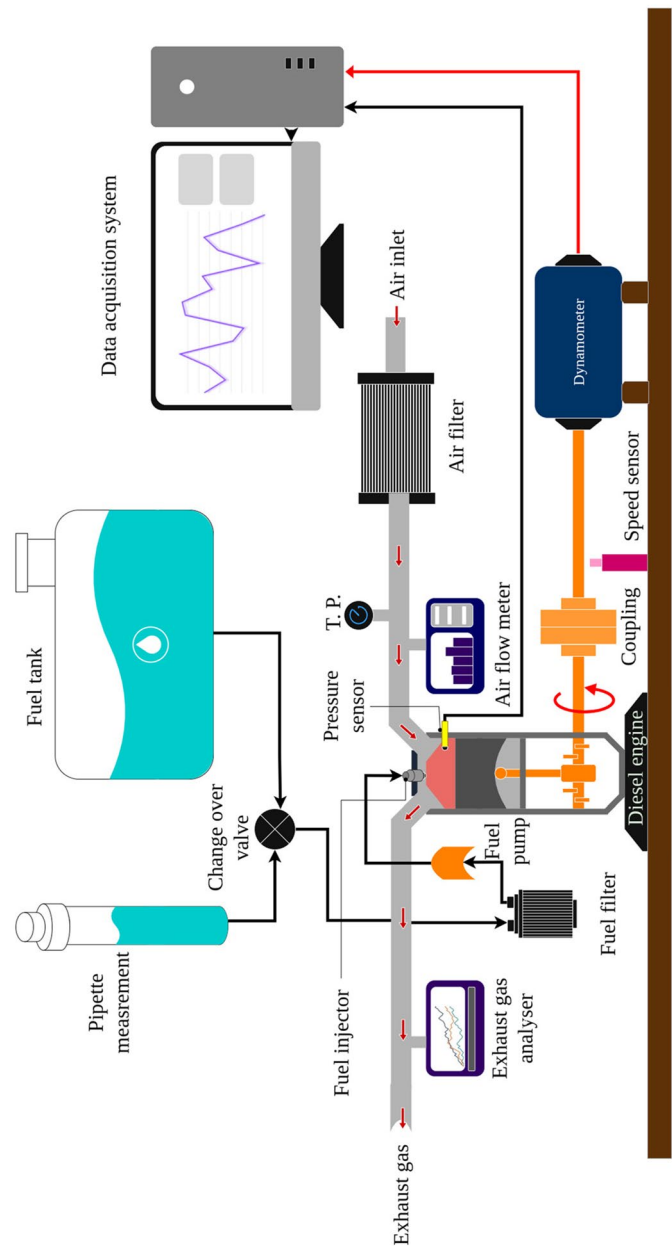


Fig. 1 Schematic view of experimental setup

practical utility in diesel engines. The properties of the fuels (diesel, B100, B20, B10, and B30) are examined in accordance with ASTM standards and presented in Table 4. The density and viscosity increase with increasing biodiesel content and with neat diesel. The B100 fuel sample exhibits higher density and viscosity and a lower calorific value than other GGG + GI-derived biodiesel blends and neat diesel. Additionally, biodiesel and its blends show higher flash and fire points than diesel fuel, ensuring compliance with safety regulations for storage and handling. The favorable fuel properties of biodiesel motivate the investigation of the performance and emission characteristics of diesel engines.

Error analysis

The tested fuels enable diesel engines to operate with minimal or no modifications. Estimating errors and uncertainties are essential to ensure the accuracy and reliability of the experimental results. Factors such as instrument selection, calibration, measurement precision, environmental conditions, data readings, observation, recording procedures, and test planning contribute to experimental errors and uncertainties. Each experiment is conducted carefully, and the average of the recorded values is calculated to reduce random errors and improve the reliability of the statistical analysis. The accuracy of all measuring instruments is evaluated prior to experimentation, and the corresponding details are presented in Table 5. The overall uncertainty (OU) is calculated based on instrument accuracy, as shown in Eq. 1. The measured uncertainty of $\pm 3.29\%$ (less than 5%) confirms the reliability and significance of the experimental results.

$$OU = \sqrt{(EL)^2 + (FFR)^2 + (CO)^2 + (BTE)^2 + (NO_X)^2 + (HC)^2 + (BSFC)^2}$$

$$OU = \sqrt{(0.48)^2 + (0.37)^2 + (1.31)^2 + (0.73)^2 + (1.82)^2 + (2.14)^2 + (0.57)^2} \quad (1)$$

$$= \pm 3.29$$

Nanoparticles and their characterization

SEM Analysis

CaO·Al₂O₃ nanoparticles (NPs) with 99.5% purity are procured from Intelligent Materials Pvt. Ltd., Punjab, India. The molecular weight, density, and specific heat capacity of the CaO·Al₂O₃ NPs are 158.0387 g/mol, 2.9 g/cm³, and 125 J/mol·K, respectively. These nanoparticles are used as additives in biodiesel-diesel blends to evaluate engine performance and emissions.

SEM morphology reveals a heterogeneous, textured oxide surface with discrete nanoparticles and porous regions, which enhance surface area and promote effective interaction between the nanoparticles and biodiesel (Fig. 2a-c).

CaO facilitates the oxidation of carbon species, thereby improving the thermal decomposition of heavier biodiesel molecules, while Al₂O₃ stabilizes the nanoparticles

Table 5 Summary results of uncertainty analysis

Factors	Accuracy	Uncertainty (%)
EL, kg	± 0.1	± 0.48
FFR, l/h	± 0.02	± 0.37
BSFC, kg/kW·h	± 0.04	± 0.57
UHC, ppm	± 1 ppm	± 2.14
BTE, %	± 0.4	± 0.73
CO, vol. %	± 0.01	± 1.31
NOx, ppm	± 1	± 1.82

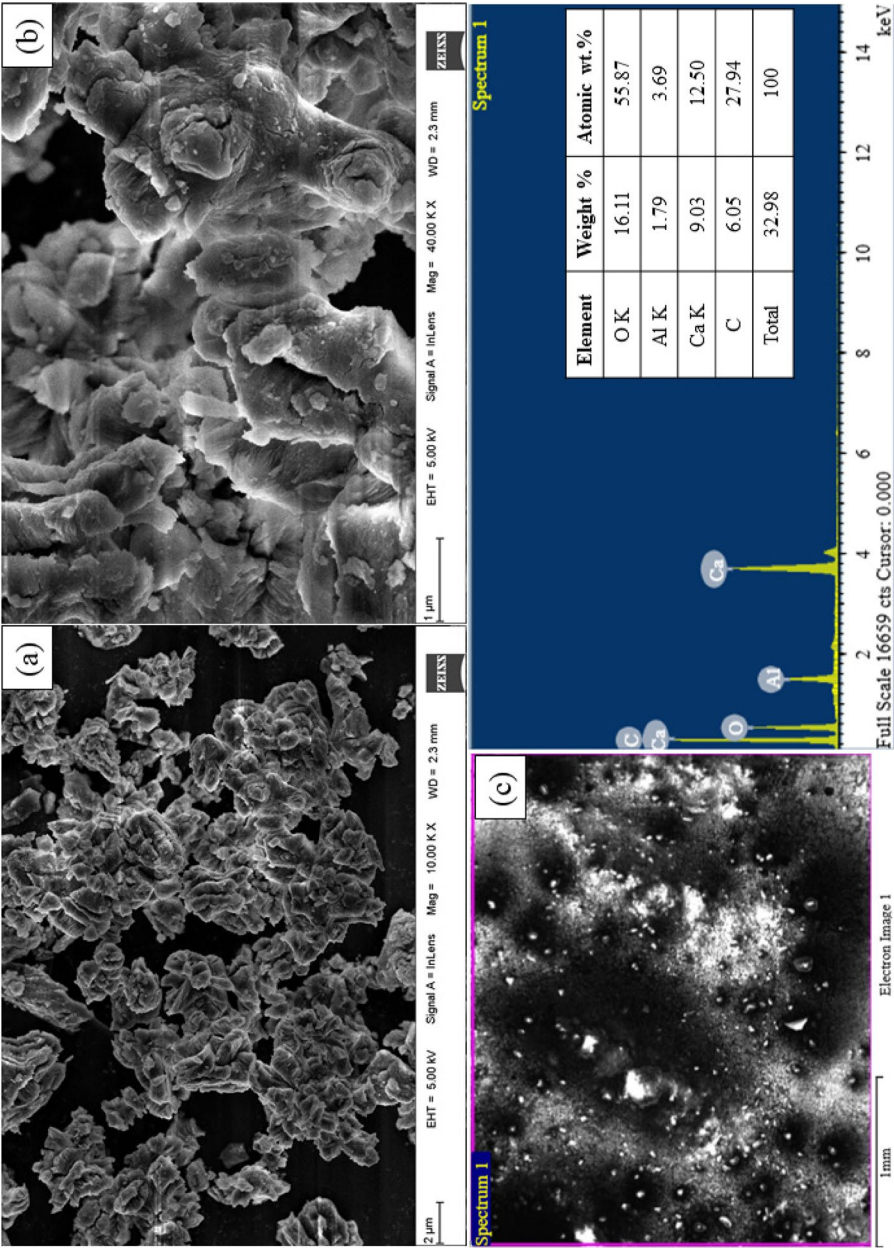


Fig. 2 Scanning electron micrographs (SEM) of $\text{CaO}/\text{Al}_2\text{O}_3$ NPs: (a) lower magnification; (b) higher magnification; (c) EDS analysis

and prevents sintering. Calcium oxide has strong basic properties and high reactivity, whereas alumina provides a high surface area and thermal stability. The hybridization of CaO and Al_2O_3 to form $\text{CaO}\cdot\text{Al}_2\text{O}_3$ (calcium aluminate) enhances catalytic performance and overall material properties, enabling better interaction with biodiesel-diesel blends and improving combustion chemistry when used as a fuel additive.

Due to their high surface area-to-volume ratio, $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles catalyze transesterification reactions more rapidly when used as heterogeneous catalysts, facilitating biodiesel production [70]. Their good reusability, cost-effectiveness, and chemical stability make them widely applicable in biodiesel research [7, 71, 72].

Doping $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles into biodiesel in different proportions enables evaluation of their influence on engine performance and emission characteristics. SEM micrographs show that the nanoparticles are highly agglomerated with a randomly distributed spherical morphology. The average particle size of the $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles is approximately 75.4 nm.

XPS analysis of $\text{Ca}\cdot\text{Al}_2\text{O}_3$

XPS analysis is conducted to examine the surface composition and oxidation states of synthesized $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs (Fig. 3a). The overall survey of XPS spectra of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs confirm the presence of elements (Ca, Al, O, and C), depicting the successful synthesis of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanocomposite without the presence of impurities. The prominent peaks (O 1s, Ca 2p, and Al 2p) demonstrate that the NPs surface is composed of metal

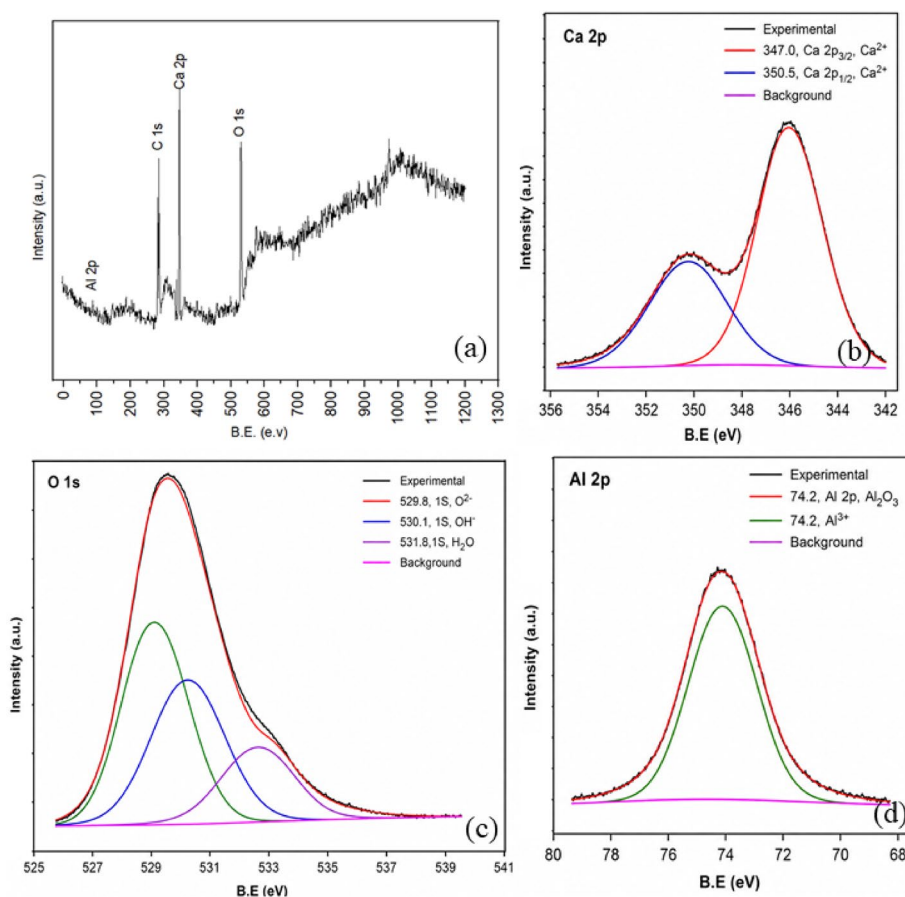


Fig. 3 (a) XPS analysis of the $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanocatalyst; (b) Ca 2p spectrum; (c) O 1s spectrum; (d) Al 2p spectrum

oxide species. The Ca 2p spectrum exhibits two characteristic peaks with binding energy at 347.0 and 350.5 eV, corresponding to Ca 2p_{3/2} and Ca 2p_{1/2}, respectively (Fig. 3b). The resulting binding energies are characteristic of Ca²⁺ species, depicting the presence of Ca in CaO. The observed doublet is consistent with CaO values, validating the successful incorporation of CaO into the nanocomposite structure. The O 1s spectrum is deconvoluted into three components centered at 529.8 (corresponds to lattice oxygen (O²⁻) associated with the oxide basis of CaO and Al₂O₃), 530.1 (associated to surface hydroxyl groups (OH⁻)), and 531.8 eV (attributed to adsorbed water molecules or surface oxygen species) (Fig. 3c). The presence of lattice oxygen and hydroxyl species indicates an oxide surface with adsorption sites. The Al 2p spectrum depicts a dominant peak located at 74.2 eV (attributed to Al³⁺ species associated with Al₂O₃) (Fig. 3d). The results are in good agreement with the published literature [73]. The presence of Al-O bonding confirms the successful formation of alumina within the NPs' matrix. Overall, the XPS results confirm the coexistence of CaO and Al₂O₃ phases on the NPs' surface and are consistent with the published literature.

Starfish Optimization Algorithm (SFOA)

The SFOA is a bio-inspired metaheuristic algorithm that mimics the natural behavior of starfish. It consists of exploration (simulating the foraging behavior of starfish) and exploitation (prey capture and regeneration to refine towards a global solution) phases to solve optimization problems. The mathematical steps involved in SFOA are explained through the following phases [47, 74]:

Initialization Phase

In SFOA, candidate solutions represented by starfish positions are randomly generated within the design search space using Eq. 2.

$$\underbrace{X_{i,j}}_{j^{\text{th}} \text{ dimension of } i^{\text{th}} \text{ starfish position}} = \underbrace{i = 1, 2, \dots, N}_{\text{Population Size}} \underbrace{\left[\text{lowerbound}_j + \text{rand}[0,1] \bullet (\text{upperbound}_j - \text{lowerbound}_j) \right]}_{\text{Design variables}} ; \text{ and } j = 1, 2, \dots, D \quad (2)$$

The fitness function value for the starfish's initial position is determined by solving the objective function using Eq. 3.

After completing the initialization phase, the SFOA enters the main loop, where it explores solutions through a combination of exploration and exploitation.

$$\underbrace{F}_{\text{Fitness value of starfish}} = \left[\begin{array}{c} F(X_1) \\ F(X_1) \\ \vdots \\ F(X_N) \end{array} \right] \quad (3)$$

Fitness value of Nth position of starfish by solving objective function

Exploration phase

In SFOA, the exploration phase utilizes a hybrid search mechanism based on the problem's dimensionality ($D > 5$ or $D \leq 5$). For $D > 5$, the search space is extensive, allowing the starfish to use all five arms to explore efficiently. The starfish arms use information about the best search position among agents to guide their movement effectively. The mathematical model for this phase is represented by Eq. 4.

$$\left\{ \begin{array}{l} Z_{i,p}^T = X_{i,p}^T + a_1 \cdot (X_{b,p}^T - X_{i,p}^T) \cdot \cos\theta, \text{rand}[0,1] \leq 0.5 \\ Z_{i,p}^T = X_{i,p}^T + \underbrace{a_1}_{(2\text{rand}[0,1]-1) \times \Pi} \cdot (X_{b,p}^T - X_{i,p}^T) \cdot \sin\theta, \text{rand}[0,1] > 0.5 \end{array} \right. \quad (4)$$

$\underbrace{Z_{i,p}^T}_{\text{Updated Position of starfish}} = \underbrace{X_{i,p}^T}_{\text{Current Position of starfish}} + \underbrace{a_1}_{(2\text{rand}[0,1]-1) \times \Pi} \cdot (X_{b,p}^T - X_{i,p}^T) \cdot \underbrace{\sin\theta}_{(\frac{\Pi}{2} \times \frac{T-T_{max}}{T_{max}})}$

In Eq. 5, p is set to 5 and randomly selected from the dimension variable D . T and T_{max} represent the current and maximum numbers of iterations, respectively. The sine and cosine terms in the equation determine the direction in which the starfish's arm twists to target food sources. The a_1 factor updates each starfish position randomly, and the value of $\theta \in \left[0, \frac{\Pi}{2}\right]$ is updated based on the number of iterations.

In the exploration phase with $D \leq 5$, it employs a unidimensional search mechanism to update the starfish's position based on the locations of other starfish targeting a food source, as in Eq. 5.

The starfish positions are updated only when better solutions are found. E_t represents the energy of the starfish.

$$\underbrace{Z_{i,q}^T}_{\text{Updated position of starfish}} = \underbrace{E_t}_{\left(\frac{T_{max}-T}{T_{max}}\right) \cdot \cos\theta} \times X_{i,p}^T + \underbrace{A_1}_{\text{rand}[-1,1]} \cdot \left(\underbrace{X_{k_1,p}^T - X_{i,p}^T}_{\text{randomly selected } p^{\text{th}} \text{ dimensional position}} \right) + \underbrace{A_2}_{\text{rand}[-1,1]} \cdot \left(\underbrace{X_{k_2,p}^T - X_{i,p}^T}_{\text{randomly selected } p^{\text{th}} \text{ dimensional position}} \right) \quad (5)$$

Exploitation phase

In the exploitation phase of SFOA, the starfish is guided by preying behaviour (adjusting the starfish's position based on the distance calculated, corresponding to the best-known solution) and a regeneration mechanism that aims to enhance the global solution. The preying behaviour process involves calculating five distances from the most prominent location to other starfish using Eq. 6, then selecting the two shortest distances to update the starfish's position using Eq. 7.

The two-dimensional search pattern in the SFOA guides some starfish towards better solutions, while others retreat in the same iteration, improving their ability to avoid local optima. Starfish are vulnerable to predation because of their slow movement, which limits their ability to escape by shedding arms. The slow movement during the regeneration phase of SFOA only applies to the last starfish ($i = N$) and is updated mathematically using Eq. 8.

$$\underbrace{d_m}_{\text{five distances between global best and other starfish}} = \left(X_{best}^T - X^T \cdot \underbrace{m_p}_{\text{five randomly selected starfish}} \right), \quad (6)$$

$m = 1, \dots, 5$

$$Z_i^T = X_{best}^T + rand_1 [0,1] \bullet \underbrace{d_{m1}}_{\text{randomly selected distance from } d_m} + rand_2 [0,1] \bullet \underbrace{d_{m2}}_{\text{randomly selected distance from } d_m} \quad (7)$$

$$Z_i^T = \exp\left(\frac{-T \times N}{T_{max}}\right) \bullet X_i^T \quad (8)$$

If the position referred to in Eq. 8 exceeds the boundaries of the design variables, it is adjusted using Eq. 9 as follows:

The regeneration phase requires fewer function evaluations and helps avoid local minima, thereby improving global convergence.

$$X_i^{T+1} = \begin{cases} Z_i^T & \text{lowerbound} \leq Z_i^T \leq \text{upperbound} \\ \text{lowerbound} & Z_i^T < \text{lowerbound} \\ \text{upperbound} & Z_i^T > \text{upperbound} \end{cases} \quad (9)$$

Grey wolf optimizer

GWO is a nature-inspired meta-heuristic swarm intelligence algorithm that mimics the social dominance structure or hierarchy and the cooperative hunting strategy of a grey wolf pack in the wild [75, 76]. The social hierarchy of grey wolves in a pack is presented in Fig. 4. The α wolves are treated as leaders in a pack (first-best fitness solution), in which they make major decisions (sleeping, hunting, encircling, and attacking), and the entire pack follows [76]. The β wolves, who are subordinate wolves (second-best solution), will assist α wolves in decision-making or guide other wolves when α wolves are sick or ill. The third-best solution is treated as δ wolves who act as scouts, sentinels,

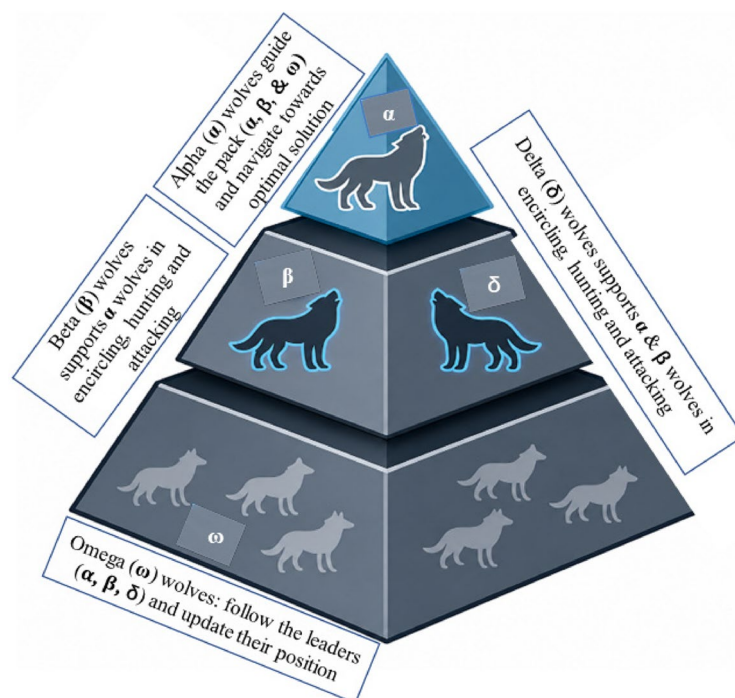


Fig. 4 Hierarchy of GWO

hunters, caretakers, and follow the instructions of α and β . The ω wolves act as scapegoats of the pack, updating their positions by following α , β , and δ . The optimization task mimics the hunting strategy of grey wolves by balancing exploration (searching for new regions, i.e., tracking, chasing, and approaching prey) and exploitation (refining existing areas, i.e., surrounding, harassing, and attacking prey). The major phases of the GWO algorithm are presented in Fig. 5.

Mathematically, the algorithm procedure is modelled using the following steps [75–77]:

1. The random population of grey wolves (candidate solutions), the maximum number of iterations, and the coefficients of the vectors (a , A , and C) are initialized within the search space.
2. The algorithm solves a mathematical equation, defined as the fitness of the objective function for an individual wolf within the defined population.
3. The fitness values for each wolf in a pack are determined and compared to define α (the first-best solution), β (the second-best solution), δ (the third-best solution), and the remaining wolves as omega wolves.
4. The grey wolves encircle prey during the hunting process and are mathematically modelled such that the positions of individual wolves are updated in accordance with the prey position (X_{Prey}) using Eqs. 10, 11.

$$D = \left| \underbrace{C}_{2 \cdot rand_2[0,1]} \bullet X_{prey}(t) - X(t) \right| = \pi r^2 \quad (10)$$

$$X(t+1) = X_{Prey}(t) - \underbrace{A}_{2a[2,0]rand_1[0,1]} \bullet D \quad (11)$$

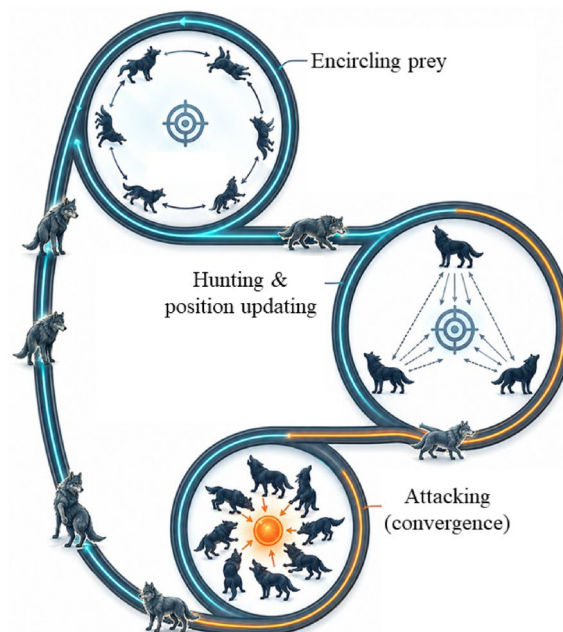


Fig. 5 Major phases of the GWO algorithm

5. The precise location of prey (global optimal) is unknown during the hunting mechanism, in which the algorithm presumes that the α , β , and δ wolves have the best knowledge of the prey's location. However, the ω wolves update their positions in accordance with the α , β , and δ wolves. The above approaches are mathematically modelled using Eqs. 12–15.

$$D_{\alpha} = |C_1 \bullet X_{\alpha} - X| \quad (12)$$

$$D_{\beta} = |C_1 \bullet X_{\beta} - X| \quad (13)$$

$$D_{\delta} = |C_3 \bullet X_{\delta} - X| \quad (14)$$

$$D_{\omega} = |C_4 \bullet X_{\omega} - X| \quad (15)$$

The direction corresponding to the individual leader is computed using the following Eqs. 16–18.

$$X_1 = X_{\alpha} - A_1 \bullet D_{\alpha} \quad (16)$$

$$X_2 = X_{\beta} - A_2 \bullet D_{\beta} \quad (17)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (18)$$

The GWO algorithm conducts an optimal search, balancing exploration and exploitation, using coefficient vectors. During the exploitation phase, the vector a linearly decreases from 2 to 0, wherein the vector A shrinks. However, the wolves converge on the prey location when the coefficient vectors $|A| < 1$ depict the local search. The wolves diverge to new locations during prey search, depicting the exploration phase, when $|A| > 1$. The vector C , whose random values range from 0 to 2, depicts the models' attempts to avoid local solutions.

Results and discussion

Data collection

Table 6 presents the experimental input–output data collected for the corresponding to GGG-GI-derived biodiesel. Each experimental trial is repeated three times, and the corresponding average values of performance (BSFC and BTE) and emission (CO, NOx, and UHC) characteristics are collected, and a parametric analysis is conducted. Note that the standard deviation and confidence intervals at 95% are computed for all five responses and are presented in Table 6. This data is used to develop second-order polynomial regression equations that model emission and performance characteristics as functions of input or engine variables. These correlations are shown in Eqs. 19–23.

$$\begin{aligned} BTE = & 12.06434 + 0.05949A + 0.022383B + 0.821109C \\ & + 0.140423D - 0.004944A^2 - 0.000046B^2 - 0.005731C^2 \\ & - 0.000048D^2 + 0.00000958333AB + 0.0011AC + 0.000264AD \\ & - 0.000247BC - 0.000021BD - 0.003165CD \end{aligned} \quad (19)$$

Table 6 CCD matrix of GGG-GI-derived biodiesel

Exp. No	Input or engine variables				Output (performance and emission) variables				
	BT, %	NPs, ppm	CR	EL, %	BTE, (%)	BSFC, kg/kW-h	CO, % Vol	UHC, ppm	NOx, ppm
1	30	60	18	100	32.362±0.241	0.21±0.005	0.09±0.002	22±2	246±3
2	10	180	14	100	33.458±0.212	0.19±0.007	0.29±0.003	69±3	164±3
3	10	60	18	40	29.356±0.123	0.24±0.007	0.21±0.005	51±3	137±4
4	30	60	18	40	27.558±0.985	0.29±0.003	0.06±0.003	18±2	169±5
5	10	180	18	100	34.885±0.993	0.17±0.005	0.24±0.003	61±3	178±5
6	20	120	14	70	29.996±1.354	0.28±0.006	0.23±0.004	57±4	158±4
7	30	120	16	70	29.332±2.122	0.27±0.004	0.10±0.001	33±2	181±4
8	10	60	14	40	27.663±2.345	0.26±0.003	0.26±0.002	58±3	128±5
9	20	60	16	70	30.445±2.109	0.26±0.003	0.25±0.003	63±3	174±3
10	20	120	16	70	31.123±1.112	0.25±0.004	0.22±0.003	54±4	167±6
11	10	120	16	70	31.883±0.543	0.23±0.005	0.25±0.004	60±1	148±5
12	30	60	14	40	25.137±0.689	0.30±0.004	0.15±0.002	34±2	151±4
13	30	180	14	40	26.223±0.934	0.28±0.006	0.11±0.002	26±3	138±5
14	30	180	18	40	28.110±0.434	0.28±0.005	0.03±0.002	13±2	147±5
15	20	120	16	40	28.452±0.185	0.28±0.003	0.19±0.003	42±3	142±3
16	20	180	16	70	31.426±0.201	0.24±0.003	0.19±0.003	47±4	160±5
17	20	120	16	100	33.665±0.176	0.22±0.004	0.23±0.003	57±5	211±4
18	30	60	14	100	31.154±0.187	0.24±0.005	0.18±0.002	40±3	220±3
19	10	180	14	40	28.336±0.122	0.25±0.002	0.22±0.003	55±3	92±4
20	30	180	18	100	32.815±0.134	0.21±0.003	0.05±0.002	16±2	228±4
21	10	60	18	100	34.121±0.112	0.18±0.003	0.26±0.002	65±3	203±4
22	10	180	18	40	30.125±0.125	0.24±0.005	0.16±0.003	38±4	96±3
23	10	60	14	100	32.935±0.203	0.20±0.006	0.36±0.004	76±3	186±4
24	20	120	16	70	31.123±0.177	0.26±0.004	0.22±0.003	54±3	167±4
25	30	180	14	100	31.884±0.165	0.24±0.002	0.13±0.002	31±2	204±3
26	20	120	16	70	31.123±0.154	0.26±0.003	0.22±0.002	54±3	167±2
27	20	120	18	70	32.162±0.134	0.26±0.004	0.17±0.002	40±3	176±2
Mean values					30.624±0.481	0.244±0.042	0.188±0.0027	45±2.89	168.07±3.93
Standard deviation					0.969	0.013	0.031	6.773	14.276
Confidence interval at 95%					30.624±0.969	0.244±0.013	0.188±0.031	45±6.773	168.07±14.276

$$\begin{aligned}
 BSFC = & 0.710717 + 0.006329A + 0.000381B \\
 & - 0.065348C + 0.001092D - 0.000095A^2 \\
 & - 0.00000222737B^2 + 0.001995C^2 - 0.000012D^2 \\
 & - 0.00000177083AB - 0.000022AC - 0.000000208333AD \\
 & + 0.00000364583BC + 0.00000100694BD - 0.000039CD
 \end{aligned} \quad (20)$$

$$\begin{aligned}
 CO = & -0.307068 + 0.013611A - 0.001456B \\
 & + 0.074722C + 0.002571D - 0.000361A^2 \\
 & + 0.00000246914B^2 - 0.002778C^2 - 0.00000123457D^2 \\
 & + 0.00000208333AB - 0.000250AC - 0.000047AD \\
 & + 0.000031BC - 0.000000694444BD - 0.000042CD
 \end{aligned} \quad (21)$$

$$\begin{aligned}
 UHC = & -195.56893 + 2.49884A - 0.219406B \\
 & + 30.97338C + 0.861934D - 0.061481A^2 \\
 & + 0.000653B^2 - 1.03704C^2 - 0.003498D^2 \\
 & - 0.00010AB - 0.059375AC - 0.010625AD \\
 & - 0.000521BC + 0.000104BD + 0.001042CD
 \end{aligned} \quad (22)$$

$$\begin{aligned}
 NOx = & -1.04527 + 1.117782A - 0.103511B \\
 & + 14.3669C - 0.888169D - 1.042963A^2 \\
 & - 0.000499B^2 - 0.449074C^2 + 0.00856D^2 \\
 & + 0.005729AB + 0.103125AC + 0.003125AD \\
 & - 0.009896BC + 0.001076BD + 0.042708CD
 \end{aligned} \quad (23)$$

Analysis of responses

A response-wise analysis is conducted to gain insights into the influencing variables affected by GGG + GI-derived biodiesel.

Response: BTE

Three-dimensional surface plots are used to analyze the two-factor interactions on BTE. The plots in Fig. 6a-c demonstrate that an increased biodiesel proportion results in a decrease in BTE due to higher viscosity, density, and surface tension, leading to poor atomization and improper air–fuel mixing, and thus slower combustion and lower BTE [78]. The interaction effect of biodiesel blend with engine load has a greater impact than nanoparticle concentration and compression ratio, with a maximum estimated value of 34.0718% (Figs. 6a-c). Increasing the nanoparticle concentration in the fuel tends to improve BTE by enhancing the nanoparticles' surface-to-volume ratio, promoting better air–fuel oxidizer contact, and improving catalytic activity.

The interaction between nanoparticle concentration and engine load yields a maximum BTE of 33.8% compared to compression ratio and blend type (Figs. 6a, d-e). The surface plot indicates that BTE increases with compression ratio and engine load, attributed to higher cylinder pressure, improved spray characteristics that favor clean and complete combustion, and a rise in cylinder temperature with a shortened ignition delay [79]. The combination of higher engine load and compression ratio values results in a maximum biodiesel conversion of 34.2303% (Figs. 6b-f).

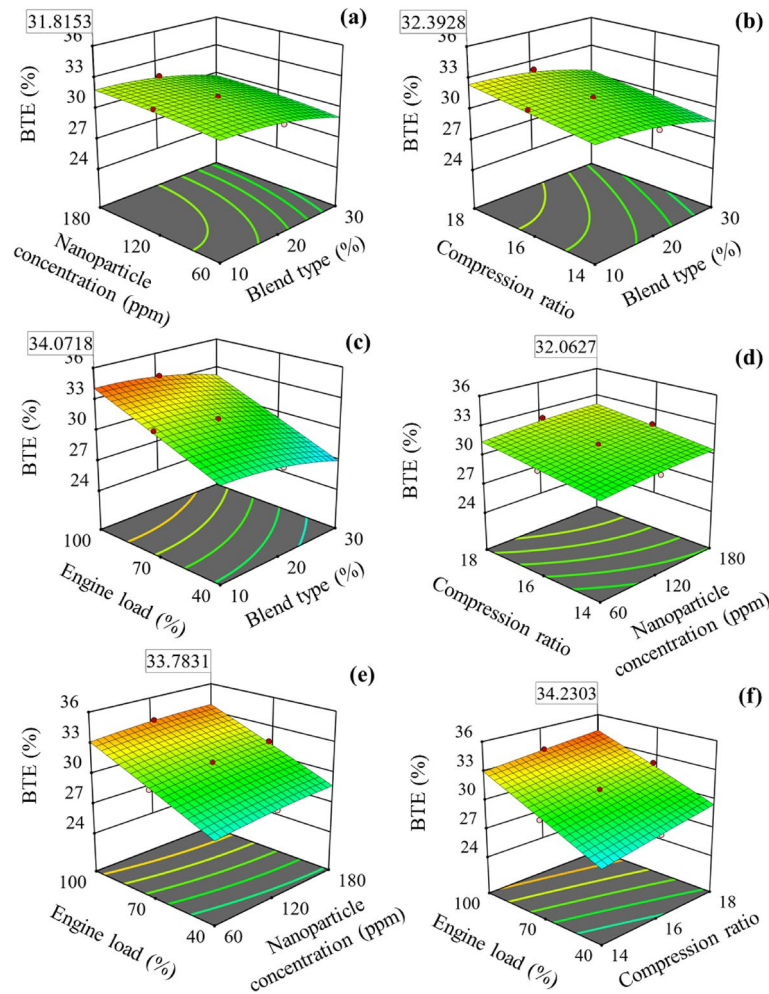


Fig. 6 Surface plots of BTE with: (a) BT and NPs; (b) BT and CR; (c) BT and EL; (d) NPs and CR; (e) NPs and EL; (f) CR and EL

Response: BSFC

Figure 7a-c shows that combining a lower blend type (10% biodiesel) with higher concentrations of NPs, CR, and EL results in lower BSFC values of 0.22, 0.23, and 0.19 kg/kW·h. Higher proportions of NPs act as oxygen promoters due to their greater surface area contact and favorable fuel characteristics, such as low viscosity and density, as well as a higher heating value. The addition of 10% biodiesel enhances combustion quality and generates higher power than 30% biodiesel [50]. The low blend type provides favorable oxygenated fuel characteristics, and a higher CR results in finer fuel droplets entering the combustion chamber, leading to better combustion efficiency and reduced BSFC [80]. The oxygenated biofuel has a high calorific value and a low blend type, which increases cylinder temperature and pressure at higher engine load. This results in an increased energy release rate and output power, leading to reduced BSFC [81]. Figure 7 d shows that combining mid-range CR values with higher NP concentrations in biodiesel results in lower BSFC values of 0.24 kg/kW·h. This is primarily due to improved characteristics such as shorter ignition delay, increased oxygen content in the air–fuel mixture, higher calorific value, and improved atomization. The combustion behavior with NPs additives in biofuel is optimized when the engine operates at a CR 16–18 [82]. Figure 7e

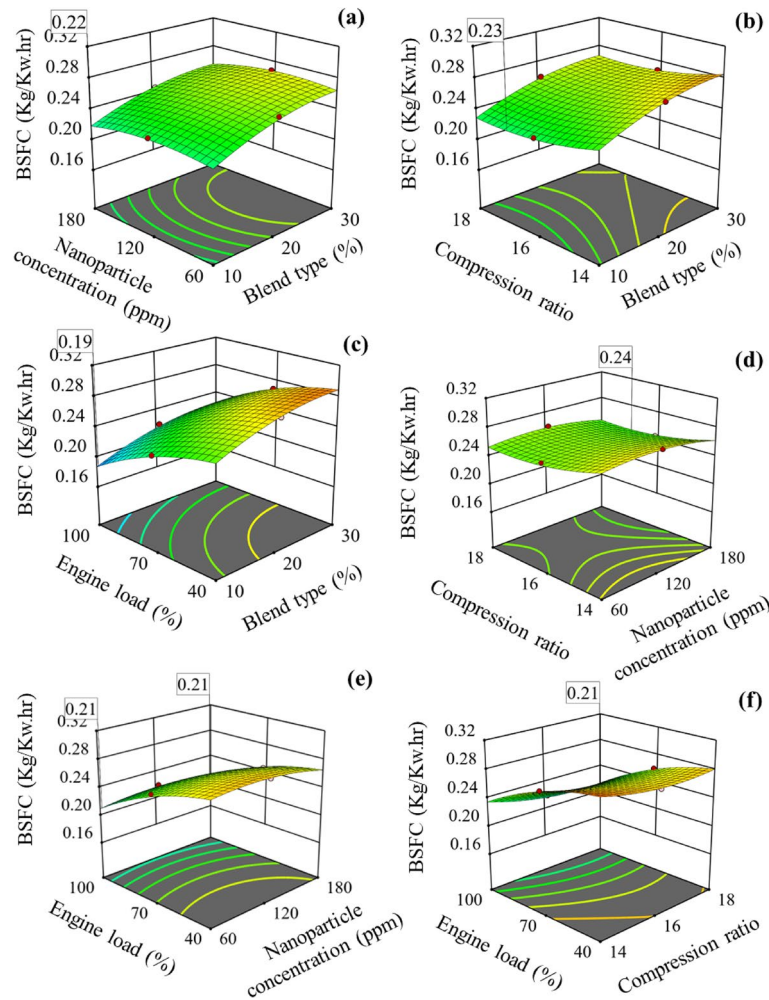


Fig. 7 Surface plots of BSFC with: (a) BT and NPs; (b) BT and CR; (c) BT and EL; (d) NPs and CR; (e) NPs and EL; (f) CR and EL

demonstrates that the combination of higher EL and NPs reduced the BSFC to 0.24 kg/kW·h. The NP additive enhanced fuel properties, raising combustion temperature and improving thermal efficiency, thereby decreasing BSFC [83]. Furthermore, the combination of higher EL and CR lowers the BSFC to 0.21 kg/kW·h (Fig. 7f), likely due to higher combustion temperature and pressure, leading to improved combustion efficiency and reduced heat-rejection losses [84, 85].

Carbon monoxide emission

Figure 8a-b shows that using a higher biodiesel percentage (30%) with NPs and CR results in reduced CO emissions of 0.093105 vol.% and 0.053 vol.%, respectively. The characteristics of NPs, such as a large surface area and oxygen promotion, along with the higher biodiesel content, lead to improved catalytic activity, resulting in better air–fuel mixture and fuel characteristics for quicker and complete combustion, thereby reducing CO emissions [50, 86]. CR increases cylinder pressure and temperature, enabling the injection of fine droplets of oxygenated fuel into the engine cylinder, enhancing combustion characteristics and reducing CO emissions. Combining lower EL and higher biodiesel content further reduces CO emissions to 0.090558 vol.% (Fig. 8c). A higher

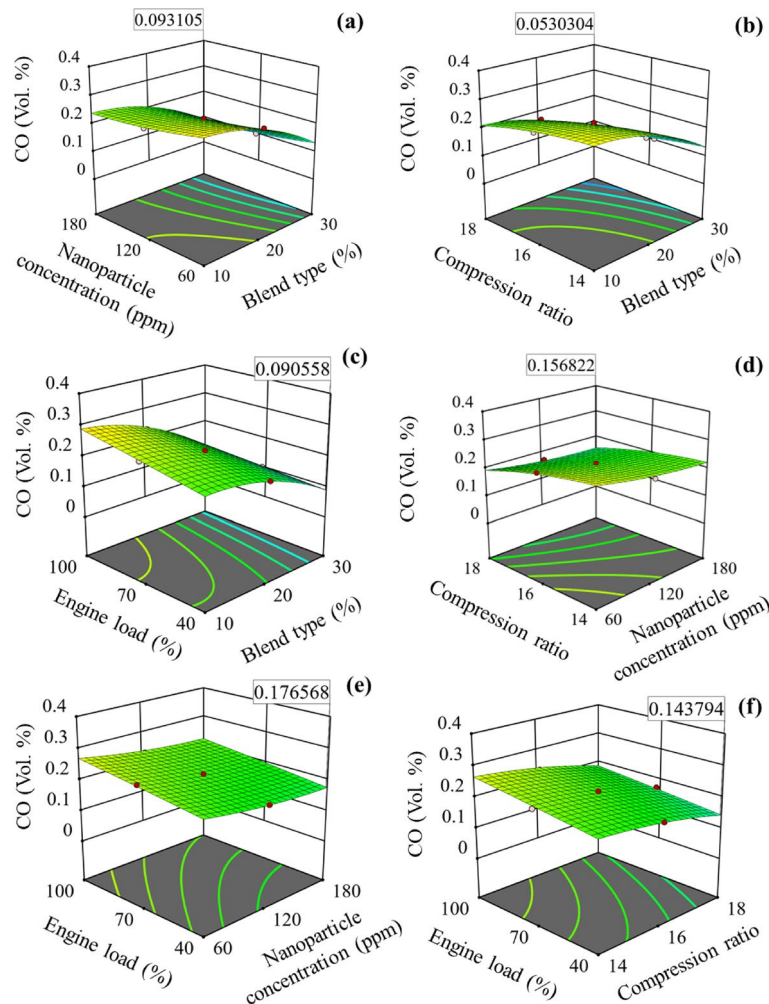


Fig. 8 Surface plots of CO with: (a) BT and NPs; (b) BT and CR; (c) BT and EL; (d) NPs and CR; (e) NPs and EL; (f) CR and EL

proportion of oxygenated biodiesel improves air–fuel mixture quality, heat transfer, and ignition characteristics at lower EL, thereby reducing CO emissions [36]. Figure 8d demonstrates that higher proportions of NPs and CR reduce CO emissions to 0.156822 vol.%. Higher CR increases air temperature and pressure in the engine cylinder, while NPs increase the contact area between the air–fuel mixture, shortening the ignition delay and ensuring complete combustion [82, 87]. Higher proportions of NPs with lower EL result in reduced CO emissions of 0.176568 vol.% (Fig. 8e). NPs enhance catalytic activity and act as oxygen promoters, improving combustion characteristics at lower fuel levels and lower EL, thereby reducing CO emissions [87]. Figure 8f shows that combining higher CR and lower EL values reduces CO emissions to 0.143794 vol.%. Increased CR raises cylinder pressure and air temperature, allowing for lower fuel injection into the engine cylinder at lower loads, ensuring complete combustion and reducing CO emissions [84].

Unburnt Hydrocarbon Emission

Figure 9a–b shows that the combination of higher values of NPs and BT, and CR and BT results in reduced UHC emission of 28.9512 ppm and 18.7322 ppm, respectively. Higher BT increases the presence of oxygen molecules with fewer carbon and hydrogen atoms,

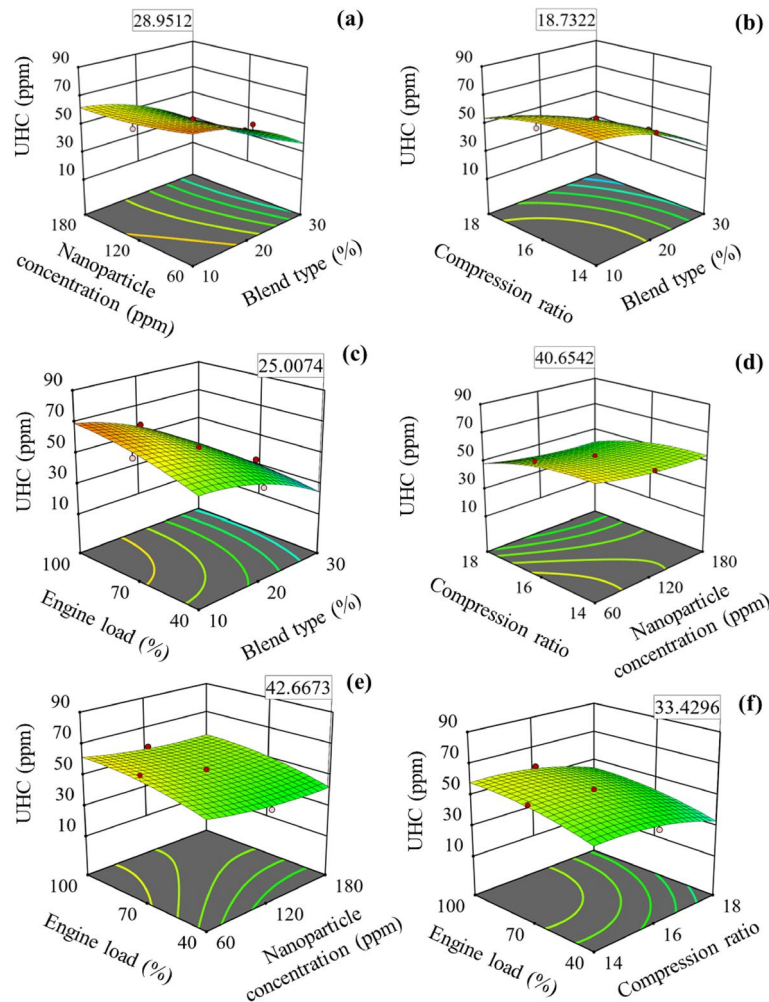


Fig. 9 Surface plots of UHC with: (a) BT and NPs; (b) BT and CR; (c) BT and EL; (d) NPs and CR; (e) NPs and EL; (f) CR and EL

while NPs act as oxidation catalysts, accelerating the oxidation of hydrocarbons. This leads to an improved air–fuel mixture, resulting in enhanced.

Higher CR, along with a sufficient supply of oxygenated fuel entering the combustion chamber, results in better combustion efficiency (higher temperature and pressure), leading to lower UHC emissions [88], as shown in Fig. 9b. The combination of higher BT and lower EL results in reduced UHC emissions of 25.0074 ppm (Fig. 9c). Lower EL provides sufficient time for the higher-oxygenated biodiesel to undergo complete combustion, ensuring a homogeneous air–fuel mixture enters the combustion chamber and reducing UHC emissions [58]. Higher values of NPs and CR results in lower UHC emissions of 40.6542 ppm (Fig. 9d). NPs act as oxidation catalysts to improve the calorific value, air–fuel mixture, and oxidation of hydrocarbons. Consequently, engine cylinder pressure and temperature increase with a higher CR, leading to reduced UHC emissions [88]. The desired reduction in UHC emissions is achieved by combining low EL and higher NPs, resulting in 42.6673 ppm (Fig. 9e). The addition of nanoparticles reduces fuel viscosity by increasing the contact area between the air–fuel mixture, ensuring complete combustion at a lower fuel quantity and, consequently, lower EL. Similar findings have been reported in the literature [84].

Reduced UHC emissions of 33.42996 ppm are observed for the combination of higher CR and lower EL (Fig. 9f). It is postulated that higher CR promotes improved air–fuel mixture and combustion efficiency, resulting in higher in-cylinder temperature and pressure at a reduced ignition delay, ensuring complete fuel oxidation and consequently leading to lower UHC emissions [89, 90].

Nitrogen Oxide (NOx) emission

A higher proportion of NPs in fuel with lower oxygen content (i.e., lower biodiesel content) leads to a decrease in NOx emissions by 128.26 ppm (Fig. 10a). The presence of NPs enhances catalytic reaction rates by increasing the contact between oxygen and the fuel. Additionally, the higher fuel viscosity and lower calorific value resulting from increased biodiesel content improve combustion characteristics and reduce NOx emissions [89, 90]. When both the BT and CR are low, NOx emissions equal 137.15 ppm (Fig. 10b). This combination is believed to increase the availability of higher-oxygen molecules with increasing biodiesel content, while a higher compression ratio enhances atomization, leading to finer fuel droplets entering the combustion chamber and raising gas temperature, thereby increasing NOx emissions.

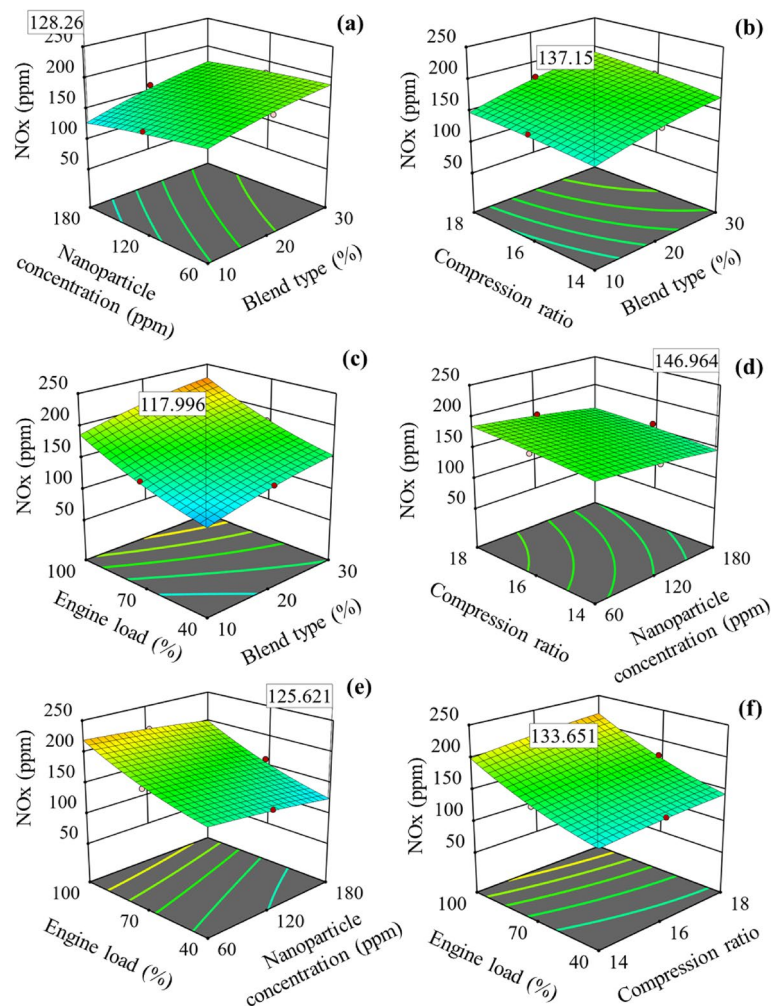


Fig. 10 Surface plots of NOx with: (a) BT and NPs; (b) BT and CR; (c) BT and EL; (d) NPs and CR; (e) NPs and EL; (f) CR and EL

A decrease in NOx emissions of 117.996 ppm is observed with the combination of low BT and EL (Fig. 10c). The presence of oxygen molecules, at lower biodiesel volume fractions and low engine load, increases cylinder pressure and lowers temperature, resulting in reduced NOx emissions [91]. A higher proportion of NPs with a lower CR results in reduced NOx emissions of 146.964 ppm (Fig. 10d). The addition of more NPs promotes secondary fuel atomization, producing ultra-fine fuel droplets that enhance premixed combustion and, with a higher compression ratio, limit cylinder pressure and temperature, thereby reducing NOx emissions. Increasing the proportion of NPs at low EL reduces NOx emissions by 125.621 ppm (Fig. 10e). Adding NPs improved the fuel properties and acted as a catalytic reactor, providing better oxidizer-fuel contact sufficient for engine operation at lower load, thereby maintaining the engine cylinder temperature and reducing NOx emissions. The combination of low CR and EL reduces NOx emissions to 133.651 ppm (Fig. 10f). This is attributed to low compression ratio values and engine load, which keep cylinder pressure and temperature low, thereby reducing exhaust NOx emissions [92].

ANOVA for responses (performance and emission characteristics)

The ANOVA test results show the full quadratic-factor effects (individual, square, and two-term interaction) on five responses, as shown in Table 7. The factors are considered significant (p -value < 0.05) at the 95% confidence level. Any change in the operating levels of significant terms may lead to potential changes in the responses. All individual terms (blend type, nanoparticle concentration, compression ratio, and engine load) are statistically significant, affecting all five responses (performance: BTE and BSFC; and emissions: CO, HC, and NOx). The contribution of individual factors to different responses is ranked as follows: EL > BT > CR > NP for BTE, EL > BT > CR > NP for BSFC, BT > CR > EL > NP for CO, BT > CR > EL > NP for UHC, and EL > BT > NP > CR for NOx emissions. The square terms of the blend type show a significant effect, indicating a strong nonlinear relationship with BTE, BSFC, CO, and UHC, but a linear relationship with NOx. Engine load has a nonlinear relationship with NOx and BSFC, and a linear relationship with BTE, CO, and UHC. Nanoparticle concentration and compression ratio show linear relationships with all responses (except BSFC).

Table 7 Model performance and significant factors for each response

Factors	BTE	BSFC	CO	UHC	NOx
Significant terms					
Individual	A, B, C, and D	A, B, C, and D	A, B, C, and D	A, B, C, and D	A, B, C, and D
Square term	A ²	A ² , B ² , C ² , and D ²	A ²	A ²	D ²
Two-term interaction	CD	CD	AD	AD	AB, AC, BD, and CD
Insignificant terms					
Individual	NIL	NIL	NIL	NIL	NIL
Square term	B ² , C ² , and D ²	NIL	B ² , C ² , and D ²	B ² , C ² , and D ²	A ² , B ² , and C ²
Two-term interaction	AB, AC, AD, BC, and BD	AB, AC, AD, BC, and BD	AB, AC, BC, CD, and BD	AB, AC, BC, CD, and BD	AD and BC
R ² term	99.64	99.26	99.33	98.46	99.58
Adjusted R ² term	99.22	98.39	98.55	96.65	99.10

Despite all individual terms being significant, only a few of their interaction effects are significant. The interaction term between compression ratio and engine load is significant for BTE, BSFC, and NOx. In contrast, the interaction between blend type and engine load is significant for CO and UHC. No significant interaction between nanoparticle concentration and injection time is observed for any of the responses. All models exhibited a high coefficient of determination (R^2), indicating their ability to predict outcomes (BTE, BSFC, CO, UHC, and NOx) closely aligned with experimental data.

Relationship between responses (performance and emission characteristics)

The third-order nonlinear relationships between the outputs are shown in Eqs. 24–33, as depicted in Figs. 11 and 12.

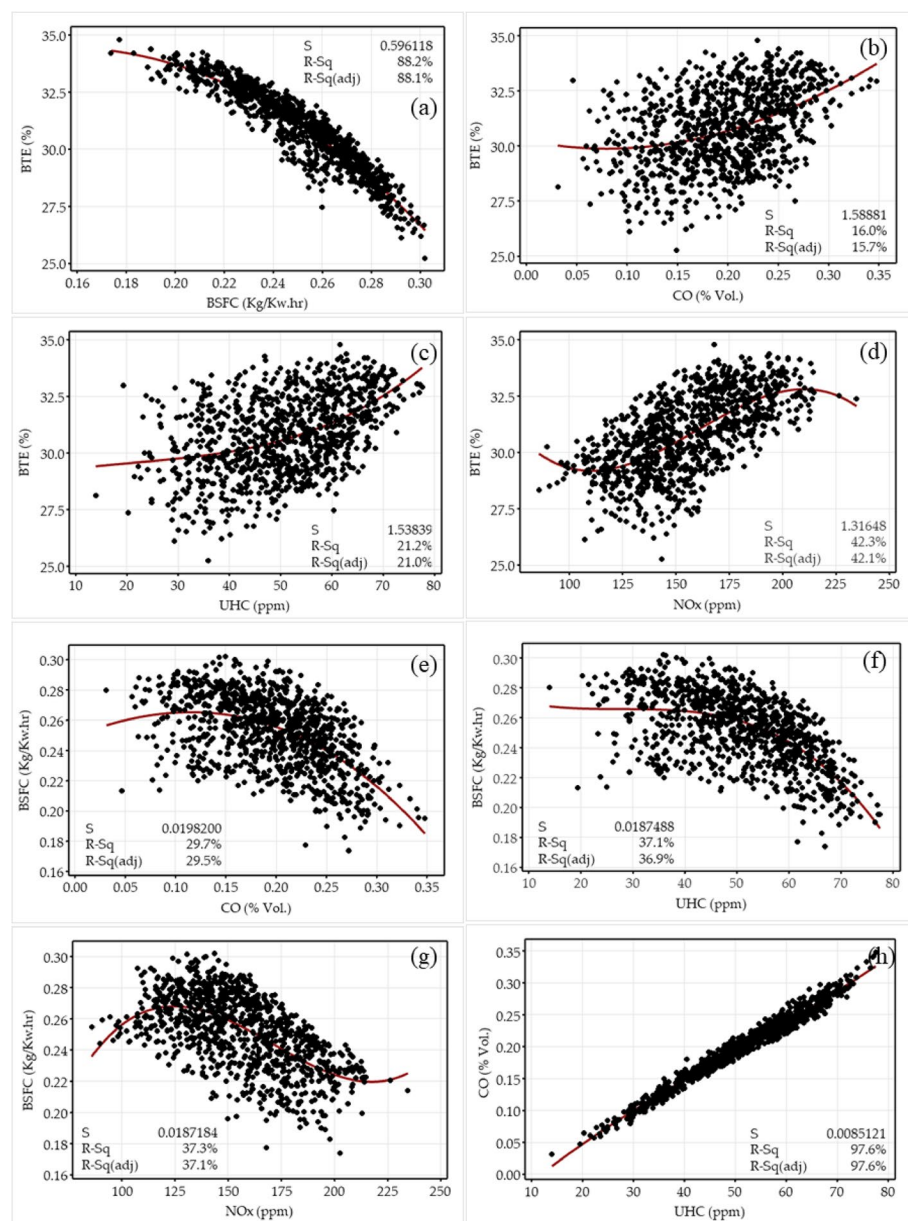


Fig. 11 Dependency among output variables: (a) BTE vs. BSFC; (b) BTE vs. CO; (c) BTE vs. UHC; (d) BTE vs. NOx; (e) BSFC vs. CO; (f) BSFC vs. UHC; (g) BSFC vs. NOx; (h) CO vs. UHC

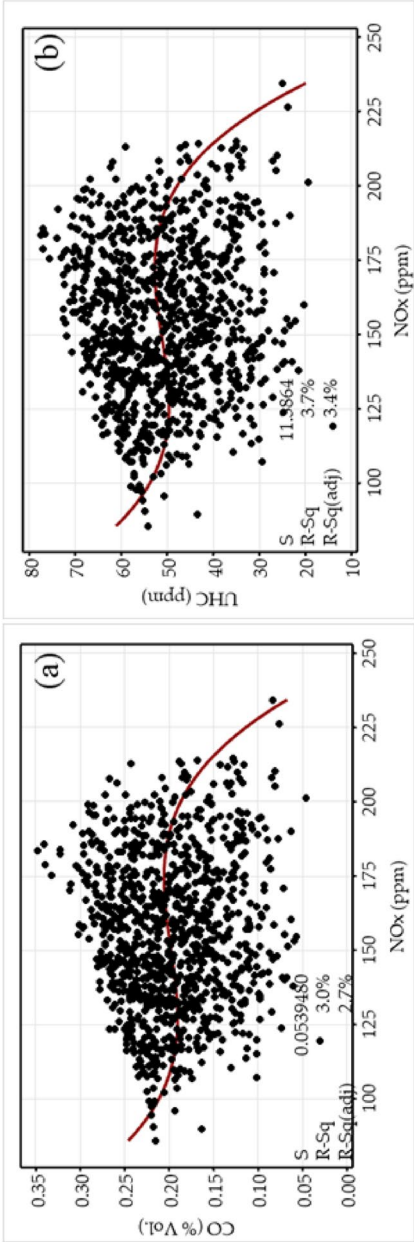


Fig. 12 Dependency among output variables: **(a)** CO vs. NOx; **(b)** UHC vs. NOx

$$BTE = 27.33 + 90.0BSFC - 258.0BSFC^2 - 164.2BSFC^3; R^2 : 88.2\% \quad (24)$$

$$BTE = 30.26 - 9.87CO + 64.26CO^2 - 21.1CO^3; R^2 : 16\% \quad (25)$$

$$BTE = 28.98 + 0.0440UHC - 0.001122UHC^2 + 0.000017UHC^3; R^2 : 21.2\% \quad (26)$$

$$BTE = 52.19 - 0.5060NOx + 0.003501NOx^2 - 0.000007NOx^3; R^2 : 42.3\% \quad (27)$$

$$BSFC = 0.2496 + 0.2614CO - 0.981CO^2 - 0.865CO^3; R^2 : 29.7\% \quad (28)$$

$$BSFC = 0.2796 - 0.001478UHC + 0.000053UHC^2 - 0.000001UHC^3; R^2 : 37.1\% \quad (29)$$

$$BSFC = 0.2259 + 0.009805NOx - 0.000062NOx^2 + 0.0000001NOx^3; R^2 : 37.3\% \quad (30)$$

$$CO = 0.08012 + 0.007307UHC - 0.000055UHC^2 + 0.0000001UHC^3; R^2 : 97.6\% \quad (31)$$

$$CO = 1.120 - 0.01932NOx + 0.000132NOx^2 - 0.0000001NOx^3; R^2 : 3\% \quad (32)$$

$$UHC = 249.9 - 4.199NOx + 0.02883NOx^2 - 0.000064NOx^3; R^2 : 3\% \quad (33)$$

The engine operates on a specific fuel and condition (Example Table 6 of Exp. No. 1), where five different outputs (BTE, BSFC, CO, UHC, and NOx) are measured in a single experimental trial. These outputs are interdependent and require quantitative estimation. One thousand sets of randomly generated input data (engine variables: BT, NPs, CR, and EL) are used to predict output data (emissions: CO, NOx, and UHC, and performance: BTE and BSFC) using regression Eqs. 19–23.

Figure 11a-h illustrates the relationships between the responses based on 1000 data patterns. BTE is expressed as a cubic nonlinear function of BSFC based on the best-fit curve shown in 2D (Fig. 11a). Similar combinatorial output relationships are established and presented in Figs. 11b-h and Fig. 12a-b. The correlation coefficient between BTE and BSFC is 0.882, indicating a strong nonlinear relationship (Fig. 11a). Figure 11a shows that BTE decreases with increasing BSFC, and vice versa.

Figure 11h illustrates the relationship between CO and UHC emissions, with a correlation coefficient of 0.976. CO emissions increase with increasing UHC. The third-order regression equations with coefficients greater than 0.8 provide accurate predictions. The relationships between BTE and BSFC and between CO and UHC have correlation coefficients exceeding 80%, making these equations suitable for correct predictions. BTE

can be predicted from known BSFC values, and CO can be predicted from known UHC values.

Multiobjective optimization of GGG + GI biodiesel on the engine performance and emission characteristics

The use of GGG + GI biodiesel in a diesel engine impacts emissions (CO, NO_x, and UHC) and performance (BSFC and BTE). Optimization aims to find optimal input variable conditions (EL, BT, NPs, and CR) that maximize BTE and minimize CO, NO_x, UHC, and BSFC. Table 8 shows the conflicting effects of input variables on the outputs. The best and worst values for each output correspond to different input variable conditions, leading to a multimodal problem with multiple optimal conditions. The SFOA and GWO methods are used to determine a single input condition for five outputs (BSFC, BTE, CO, NO_x, and UHC).

Mathematical formulation of the problem

The multiobjective optimization task requires a single input variable to be optimized to produce five outputs with conflicting objectives (Maximize: BTE; Minimize: BSFC, CO, NO_x, and HC). Six case studies are conducted using different weight fractions (W₁, W₂, W₃, W₄, and W₅ correspond to BTE, BSFC, CO, HC, and NO_x) to solve multiple-objective optimization tasks. Case 1 (W₁ to W₅=0.2) assigns equal importance to all outputs, and Cases 2–6 assign maximum weight fraction to one output while maintaining the rest at the lowest weight fraction. Case 2 (W₁=0.6; W₂ to W₅=0.1), Case 3 (W₂=0.6; W₁, W₃ to W₅=0.1), Case 4 (W₃=0.6; W₁, W₂, W₄, W₅=0.1), Case 5 (W₄=0.6; W₁, to W₃, W₅=0.1) and Case 6 (W₅=0.6; W₁ to W₄=0.1). The MATLAB software platform is used to solve single-objective functions comprising five empirical regression equations (Eqs. 19–23) to derive optimal solutions (enhanced performance and emission reductions) using GWO and SFOA. Six case studies with assigned weights for the objective functions are used to determine optimal solutions. The mathematical formulation uses weighted objective functions for maximization, as shown in Eqs. 19–23 representing different output functions in the optimization problem.

The objective functions are subject to constraints on the input variables. To perform multiobjective optimization, the objective functions are transformed into single-objective functions for maximization using the desirability function approach (Eq. 34). The composite desirability value, computed from the individual objective functions (Eq. 35), ranges from 0 to 1. The starfish algorithm aims to determine the maximum value of Do.

Table 8 Input variables influencing outputs

Input variable	Performance Characteristics	Emission Characteristics	Reference Figure
Increase in BT (10–30%)	↑ in BSFC, ↓ BTE	↑ in NO _x , ↓ CO, UHC	Figures 6-10a-c
Increase in NPs (60–180 ppm)	↑ in BTE, ↓ BSFC	↓ in NO _x , CO, UHC	Figures 6-10a, d, e
Increase in CR (14–18)	↑ in BTE, ↓ BSFC	↑ in NO _x , ↓ CO, UHC	Figures 6-10b, d, f
Increase in EL (40–100%)	↑ in BTE, ↓ BSFC	↑ in NO _x , ↑ UHC, ↑ CO	Figures 6-10c, e, f

$$\begin{aligned}
10 &\leq BlendType \text{ or } A \geq 30 \\
60 &\leq Nanoparticle \text{ particle concentration } \text{ or } B \geq 180 \\
14 &\leq CompressionRatio \text{ or } C \geq 18 \\
40 &\leq EngineLoad \text{ or } D \geq 100
\end{aligned}$$

$$D_o = \sqrt[5]{d_{BTE}^{W_1} \times d_{BSFC}^{W_2} \times d_{CO}^{W_3} \times d_{UHC}^{W_4} \times d_{NOx}^{W_5}} \quad (34)$$

$$\left. \begin{aligned}
d_{BTE} &= \frac{BTE - BTE_{min}}{BTE_{max} - BTE_{min}} \\
d_{BSFC} &= \frac{BSFC - BSFC_{min}}{BSFC_{max} - BSFC_{min}} \\
d_{CO} &= \frac{CO - CO_{min}}{CO_{max} - CO_{min}} \\
d_{UHC} &= \frac{UHC - UHC_{min}}{UHC_{max} - UHC_{min}} \\
d_{NOx} &= \frac{NOx - NOx_{min}}{NOx_{max} - NOx_{min}}
\end{aligned} \right\} \quad (35)$$

The best and worst values of five objective functions (BTE, BSFC, CO, NOx, and HC) are determined by solving the empirical regression equations individually using GWO and SFOA. Table 9 presents the best and worst values of individual responses along with their corresponding input variable conditions.

The performance of algorithms (solution accuracy and convergence time) is influenced by parameters such as population size and the maximum number of iterations. Using a smaller population size led to premature convergence, resulting in solutions trapped in local minima. The exploration capabilities improve with larger population sizes, increasing the likelihood of finding global solutions and enabling algorithms to avoid getting trapped in local optima. However, the larger population requires an objective function to be evaluated multiple times per iteration, resulting in increased computational time and efforts [93]. Setting the maximum number of iterations too low can cause the algorithm to terminate prematurely before it converges to the global solution [16, 94]. On the contrary, computational resources (time and effort) are wasted after the maximum

Table 9 Optimal conditions for a single objective function

Optimization	Best Condition		Worst Condition	
	Input Variable	Output value	Input Variable	Output value
BTE	BT: 10.86%	34.80%	BT: 30%	25.15%
	NP: 173.3 ppm		NP: 60 ppm	
	CR: 18		CR: 14	
	EL: 100%		EL: 40%	
BSFC	BT: 10%	0.172	BT: 30%	0.305 kg/kW-h
	NP: 60 ppm	kg/kW-h	NP: 92.2 ppm	
	CR: 17.4		CR: 14	
	EL: 100%		EL: 40%	
CO	BT: 30%	0.031 Vol. %	BT: 10%	0.348 Vol. %
	NP: 174.8 ppm		NP: 60 ppm	
	CR: 18		CR: 14	
	EL: 40%		EL: 100%	
UHC	BT: 30%	13.82 ppm	BT: 10%	78.08 ppm
	NP: 174.4 ppm		NP: 60 ppm	
	CR: 18		CR: 14.68	
	EL: 40%		EL: 100%	
NOx	BT: 10%	92 ppm	BT: 30%	246 ppm
	NP: 180 ppm		NP: 60 ppm	
	CR: 18		CR: 18	
	EL: 40%		EL: 100%	

fitness value (Do value) is reached [16, 94]. To date, no universally accepted standard methods have been established in the literature for determining the optimal population size and the maximum number of iterations. Therefore, the present work conducted a systematic parametric study by varying population size (10–100) and the maximum number of iterations (10–100). Both algorithms determined identical fitness values (Do values) for each case study, with Do values equal to 0.891 for Case 1, 0.935 for Case 2, 0.922 for Case 3, 0.938 for Case 4, 0.932 for Case 5, and 0.933 for Case 6. Case 4 resulted in the highest Do value, and hence the results of the parametric study are shown in Fig. 13. Primarily, the population size was varied between 10 and 100 (with a step size of 10), after keeping the maximum number of iterations fixed at 50, and their Do values were evaluated. The GWO and SFOA converge at identical population size with a maximum Do value of 0.929 for GWO, and 0.930 for SFOA, respectively (Fig. 13a and b). However, both algorithms converged to the highest D_o value of 0.9383, with SFOA requiring the minimum number of iterations of 69 compared to 93 for GWO (Fig. 13c). The computational cost is measured as the maximum number of function evaluations (the product of the population size and the number of iterations towards global convergence) [95]. The computed maximum number of function evaluations (population size and iterations) for GWO and SFOA is 7740 and 5520, respectively. The computation time required for the MATLAB code that runs on an Intel Core i3 @ 1.2 GHz CPU and 4 GB RAM converged to a global fitness value of 8 s for GWO and 5 s for SFOA.

Table 10 presents the results of six case studies along with their composite desirability values. Case 4 is identified as the optimal condition with a desirability value of 0.938, close to 1. Experiments are carried out for Case 4 under the following conditions: BT: 29.12%, NP: 178.79 ppm, CR: 18, and EL: 55.42%. The results show BTE, BSFC, CO, NO_x, and UHC values of 30.65%, 0.285 kg/kW·h, 0.055 Vol.%, 22.4 ppm, and 165 ppm, respectively. The absolute percent deviation in prediction is 3.46% for BTE, 5.26% for BSFC, 8.33% for CO, 9.87% for NO_x, and 2.35% for UHC. The average absolute percentage deviation in prediction is 5.85%.

Comparative assessment of GGG + GI biodiesel with and without CaO.Al₂O₃ nanoparticles

In addition, experiments are conducted to examine the efficacy of biodiesel blends with and without CaO.Al₂O₃ NPs corresponding to the optimal condition of Case 4 (Table 10). The addition of CaO.Al₂O₃ NPs increase the BTE by 11.86% and reduce BSFC, CO, and UHC by 1.72%, 38.89%, and 26.80%, respectively (Table 11). The improved atomization and nanoscale catalytic activity with CaO.Al₂O₃ NPs promote complete oxidation of fuel, surface oxides facilitate enhanced interaction with biodiesel-diesel fuel molecules serving as activation sites for improved combustion, thereby reducing UHC and CO formation. It is noteworthy that NO_x emissions increased slightly (approximately 7.49%) with CaO.Al₂O₃ NPs due to improved combustion efficiency (higher flame temperatures) as a result of higher oxygen content in biodiesel blends, fuel heating or calorific value, and air–fuel ratio [96, 97]. The increased cylinder temperature during the combustion process generates a large amount of nitrogen and oxygen in the cylinder and promotes chemical reactions [98]. Similar observations of increased NO_x emissions are reported with CeO₂ [99], Al₂O₃ [96, 98], ZnO, Al₂O₃, TiO₂, MWCNTs, and MgO [97, 100]. Significant improvement in emission and performance characteristics with the addition of CaO.Al₂O₃ NPs confirming the efficacy of multiobjective optimization and

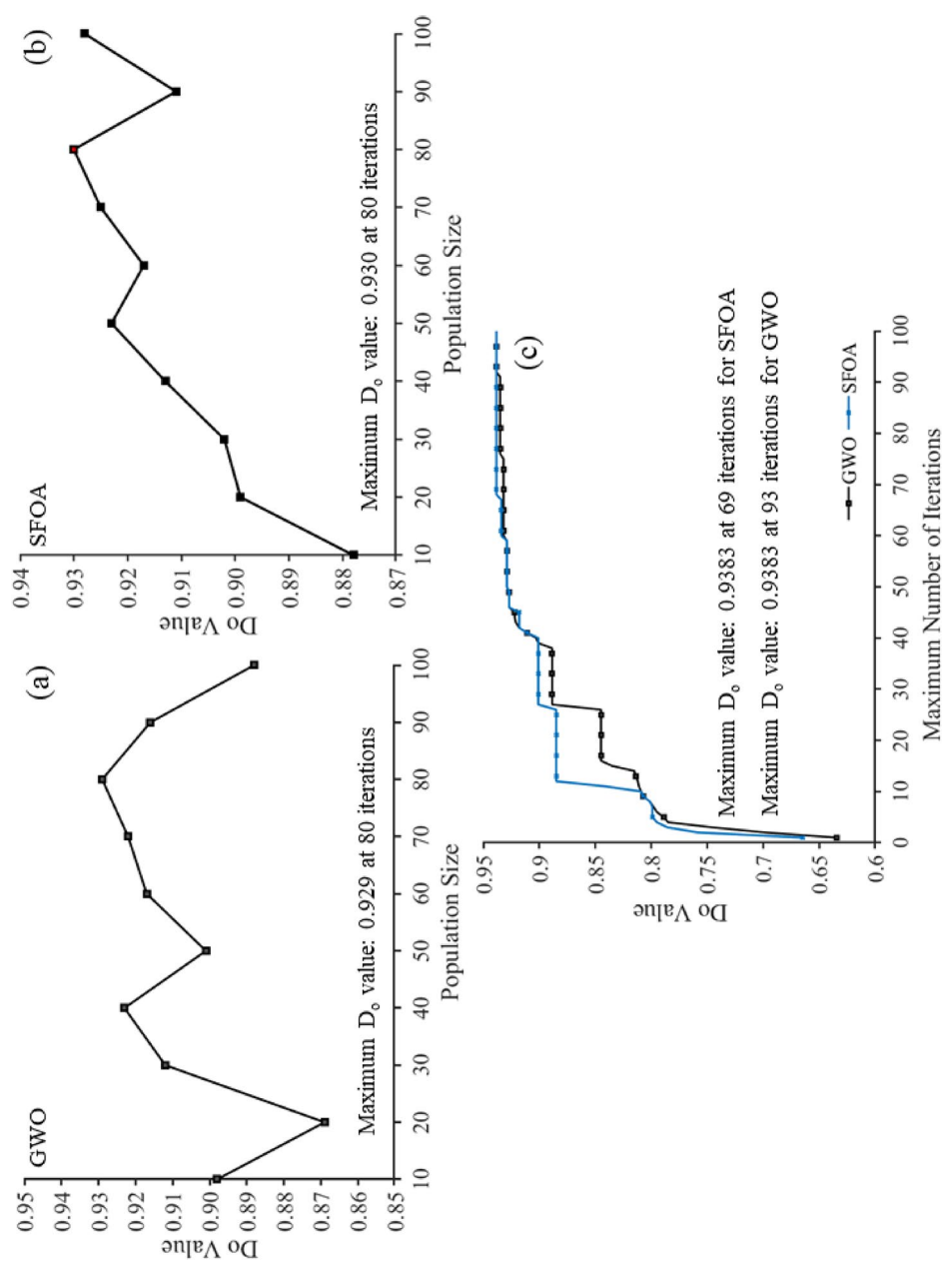


Fig. 13 Convergence plot of two algorithms (GWO and SFOA): **(a)** GWO population size vs. Do value; **(b)** SFOA population size vs. Do value; **(c)** Maximum number of iterations vs. Do value

Table 10 Case studies for multiobjective optimization solved by GWO and SFOA

Case Study	Input variables				Output variables					Desirability value
	BT, %	NPs, ppm	CR	EL, %	BTE, %	BSFC, kg/kW-h	CO, Vol. %	UHC, ppm	NOx, ppm	
Case 1	24.45	153.16	17.91	84.32	32.61	0.24	0.12	36.43	196.58	0.891
Case 2	17.79	176.45	17.98	95.18	34.19	0.21	0.19	50.91	193.62	0.935
Case 3	12.1	157.21	17.88	99.38	34.7	0.19	0.23	59.81	189.02	0.922
Case 4	29.12	178.79	18.00	55.42	29.59	0.27	0.05	20.19	161.13	0.938
Case 5	29.73	179.7	17.86	40.2	28.14	0.28	0.04	15.82	146.75	0.932
Case 6	10.17	163.48	17.32	40.94	29.99	0.25	0.18	47.71	106.18	0.933

Table 11 Comparison of optimal conditions with and without the addition of CaO.Al₂O₃ NPs

NPs	Input variables				Output variables				
	BT, %	NPs, ppm	CR	EL, %	BTE, %	BSFC, kg/kW-h	CO, Vol. %	UHC, ppm	NOx, ppm
With CaO.Al ₂ O ₃	29.12	178.79	18.00	55.42	30.65	0.285	0.055	22.4	165
Without CaO.Al ₂ O ₃	29.12	NIL	18.00	55.42	27.4	0.29	0.09	30.6	153.5
Absolute change in performance and emissions (with and without CaO.Al ₂ O ₃)					3.25	0.005	0.035	8.2	11.5
Percentage improvement in performance and emissions (with CaO.Al ₂ O ₃)					↑11.86%	↓1.72%	↓38.89%	↓26.80%	↑7.49%

The results of optimized concentration of CaO.Al₂O₃ nanoparticles confirm the balanced performance and emission characteristics with GGG+GI biodiesel blends. However, introducing nanoparticles into biodiesel blends results in increased friction and wear on various engine components [101, 102]. Therefore, detailed tribological examinations are essential to evaluate the durability of engine parts [103]

Table 12 Comparative evaluation of the DFA values of different feedstocks, driven biodiesel, and NPs

Feedstock	NPs	Methods employed	Desirability value	References
WCO	ZnO	CCRD and DFA	0.8853	[49]
Jojoba	Fe ₂ O ₃	RSM and DFA	0.7459	[37]
Spirulina microalgae	Fe ₃ O ₄	RSM and DFA	0.8299	[54]
Spirulina microalgae	BaTiO ₃	CCD and DFA	0.7449	[35]
Microalgae	Fe ₃ O ₄	CCD, ML, and DFA	0.9100	[56]
GI + GGG	CaO.Al ₂ O ₃	SFOA, GWO, and DFA	0.9383	This study

the nanoparticle and its concentration. Therefore, GGG-GI-derived biodiesel is doped with CaO.Al₂O₃ NPs can be used to run diesel engines under experimentally validated optimal conditions.

Comparative assessment of GGG + GI biodiesel with other biodiesel feedstocks (DFA)

Table 12 presents comparative assessments of different feedstocks, NPs, and methods based on the desirability function values. The target is to improve the overall desirability function value (comprising the maximum values of BTE and the minimum values of BSFC, CO, HC, and NOx) by solving Eq. 34 using the SFOA and GWO algorithms. Note that the Do value varies significantly from one research work to another, probably due to differences in biodiesel fuel properties, the parameters or variables chosen, the relative weights assigned to individual responses, and the techniques used by researchers. Furthermore, the different algorithms employ different search mechanisms, wherein these algorithms (tuning algorithm-specific and common parameters) influence the optimal settings and corresponding Do values. However, algorithms derived solutions with the

highest D_o value depict a better balance between the multiple conflicting responses. Noteworthy that the SFOA and GWO determined identical optimal conditions with the highest D_o value of 0.9383. The present work achieved the highest D_o value compared to other works are attributed to the following reasons: a) selected most competitive algorithms (SFOA: outperformed more than 95 algorithms in terms of solution accuracy for 65 benchmark functions [47], widely applied for biodiesel research GWO [16, 36, 39, 93]), b) systematic tuning of algorithm specific and common parameters that could able to achieve highest global D_o value, c) model derived empirical regression equations for five responses with better coefficient of determination value (refer to Table 7) enable the algorithms to precisely predict the global optimal conditions, d) $\text{CaO} \cdot \text{Al}_2\text{O}_3$ driven catalytic efficiency helps to improve the fuel characteristics, resulting in better performance and emission characteristics.

Sustainability assessments of present work

The present work uses two underutilized forest-based GGG + GI feedstocks to produce biodiesel, reducing dependence on fossil fuels and edible oils and thereby addressing the food vs. fuel concerns. Furthermore, blending MOFs ensures a continuous supply of locally available feedstock for biodiesel production, reduces price fluctuations, logistics, and feedstock costs, generates revenue for farmers, and provides customized fuel properties necessary for improved performance and emission reductions. The MOFs (GGG + GI) biodiesel blended with bifunctional $\text{CaO} \cdot \text{Al}_2\text{O}_3$ nanoparticles promote sustainable processing that improves fuel quality, ensuring complete combustion and better engine performance, and reducing emissions (CO, HC, and NOx) that mitigate climate change [103, 104]. The emission reductions reduce the harmful pollutants, contributing to improved air quality and reduced public health [105]. Furthermore, optimizing the engine variables (EL, NPC, BB, and CR) promotes sustainability by collectively improving combustion patterns, minimizing fuel consumption and emissions, and enhancing engine performance [106, 107]. The established framework, utilizing underutilized binary feedstock-driven biodiesel, bifunctional NPs, and optimization tasks, contributes to improved energy security, reduced environmental pollution, and, collectively, supports cleaner and more sustainable fuel for transport systems.

Conclusion

This study develops and validates a comprehensive experimental-statistical-AI framework to evaluate and optimize the performance and emission characteristics of a compression ignition engine fueled with binary biodiesel derived from *Garcinia gummi-gutta* (GGG) and *Garcinia indica* (GI), doped with $\text{CaO} \cdot \text{Al}_2\text{O}_3$ nanoparticles. Microwave-assisted transesterification produces biodiesel with a 98.9% conversion efficiency, and the measured physicochemical properties of B10, B20, and B30 blends meet ASTM standards, confirming their suitability for direct use in diesel engines. The overall experimental uncertainty of $\pm 3.29\%$ demonstrates the reliability and repeatability of the obtained data.

SEM morphology reveals a heterogeneous, textured oxide surface with discrete nanoparticles and porous regions in $\text{CaO} \cdot \text{Al}_2\text{O}_3$ nanoparticles. The XPS analysis confirms the coexistence of CaO and Al_2O_3 phases on the nanoparticle surface. The XPS results reveal the presence of lattice oxygen, hydroxyl groups, and adsorbed oxygen

species together with oxidation states (Ca^{2+} and Al^{3+}), demonstrating successful synthesis of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs and validating the oxide nature of the synthesized material.

All four control parameters, blend ratio, nanoparticle concentration, compression ratio, and engine load, significantly influence both performance (BTE and BSFC) and emission characteristics (CO, UHC, and NOx). Engine load emerges as the dominant factor affecting BTE and BSFC, while blend ratio predominantly governs CO and UHC emissions. Nanoparticle concentration consistently enhances combustion behavior. Increasing the biodiesel fraction reduces CO and UHC emissions due to its inherent oxygen content, whereas higher compression ratio and engine load improve brake thermal efficiency but tend to increase NOx emissions, highlighting the intrinsic trade-off among responses.

The addition of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ nanoparticles enhances combustion efficiency through catalytic oxidation and improved oxygen availability. Under optimized conditions, nanoparticle doping increases BTE by 11.86% and reduces BSFC, CO, and UHC by 1.72%, 38.89%, and 26.80%, respectively, while causing a marginal 749% increase in NOx emissions. Significant improvement in emission and performance characteristics with the addition of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs confirming the efficacy of multiobjective optimization and the nanoparticle and its concentration.

The integrated CCD, DFA, and SFOA framework successfully determines optimal multiobjective operating conditions, achieving a maximum desirability of 0.938. Experimental validation shows an average absolute deviation of 5.85%, confirming the predictive accuracy and robustness of the developed regression-AI model. The strong nonlinear correlations identified between key responses, particularly BTE-BSFC and CO-UHC, further strengthen the reliability of predictive modeling. The results of the integrated framework for utilizing underutilized binary feedstock-driven biodiesel, bi-functional NPs, modelling, and optimization tasks contribute to improved engine performance and reduced emissions, energy security, and economic viability, collectively supporting cleaner, more sustainable fuel for the transport system.

Scope for future work

The present work can be extended with a focus on combining $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs based biodiesel fuels with EGR, injection timing optimization, and after-treatment technologies for further enhancement in emission reductions. Furthermore, long-term stability (characterized through zeta potential analysis, sedimentation studies, and storage-duration effects) of $\text{CaO}\cdot\text{Al}_2\text{O}_3$ NPs and their negative impact on engine wear, clogging, and increased NOx emissions require stringent tribological testing to ensure feasibility for scale-up production and operation in a diesel engine.

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None

Statement

Authors have used the NotebookLM to generate the image corresponding to the Grey Wolf Images to enhance the visualization and understand the algorithm insights.

Authors' contributions

Ajith B S: Conceptualization, Formal Analysis, Investigation, Methodology, Validation, Writing-original draft; Manjunath Patel G C: Conceptualization, Formal Analysis, Investigation, Validation, Software, Supervision, Writing-original draft, Writing-review & editing; Selçuk Sarıkoç: Conceptualization, Data curation, Formal Analysis, Methodology, Validation, Writing-review & editing; Olusegun D. Samuel: Data curation, Formal Analysis, Methodology, Validation, Supervision, Writing-review & editing; Manjunath Shettar: Formal Analysis, Data curation, Methodology, Validation, Writing-review & editing. All authors have read and agreed to the published version of the manuscript.

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Data availability

The data that support the findings of this study are available within the article.

Declarations**Competing interests**

The authors declare that they have no competing interests.

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