

Optimizing Bio-Diesel Combustion and Emissions Through Artificial Intelligence Techniques.

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Abstract: The global transition toward sustainable energy has accelerated interest in alternative fuels such as biodiesel, valued for its renewability and environmental advantages. This study investigates the performance and emission characteristics of biodiesel in comparison to conventional diesel, emphasizing the application of Artificial Intelligence (AI) for predictive modeling. Machine learning techniques—including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests—are utilized to model key engine parameters such as brake thermal efficiency (BTE), brake-specific fuel consumption (BSFC), and emissions including carbon monoxide (CO), and nitrogen oxides (NOx). The findings reveal that while biodiesel blends tend to produce slightly lower power output, they achieve notable reductions in CO and hydrocarbon emissions, with a corresponding increase in NOx levels. The AI models demonstrate strong predictive capabilities across diverse operating conditions, facilitating the optimization of fuel blends and engine settings. This integration of AI into biodiesel research presents a promising pathway for enhancing the environmental and operational performance of internal combustion engines.

Keywords- Biodiesel, AI, ANN, SVM, Random Forests,

I. Introduction

The growing concerns over environmental degradation, depleting fossil fuel reserves, and increasing energy demands have propelled the global community to seek cleaner and more sustainable alternatives to petroleum-based fuels. Among these alternatives, biodiesel—a renewable, biodegradable, and non-toxic fuel derived from vegetable oils, animal fats, or waste cooking oil—has emerged as a promising candidate. Biodiesel not only offers the advantage of reducing greenhouse gas emissions but also contributes to energy security and rural economic development.

Biodiesel can be used in conventional diesel engines either in pure form (B100) or blended with petroleum diesel (e.g., B20, B50), without requiring major modifications. Despite these advantages, biodiesel usage presents certain challenges in engine performance and emission characteristics. It typically results in slightly higher brake-specific fuel consumption (BSFC) and NOx emissions, though it significantly reduces carbon monoxide (CO), unburned hydrocarbons (HC), and particulate matter (PM). Understanding and optimizing these trade-offs is crucial for widespread biodiesel adoption.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have opened new avenues for addressing complex problems in engineering, including internal combustion engine performance analysis and emission prediction. AI models can analyze vast datasets to uncover hidden patterns, enabling accurate predictions of engine behavior under varying operating conditions and fuel blends. These tools also help optimize engine parameters, fuel composition, and operating strategies to achieve better performance and lower emissions.

This study aims to investigate the performance and emission characteristics of biodiesel using AI-based modeling techniques. By integrating experimental data with predictive algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests, this research seeks to enhance the understanding of biodiesel behavior in diesel engines. The ultimate goal is to support cleaner, more efficient fuel usage while paving the way for smarter, AI-driven engine design and control strategies.

II. Literature Review

Research on biodiesel as a sustainable alternative fuel for compression ignition (CI) engines has evolved significantly over the past two decades. Initial studies focused on fundamental physicochemical characterization and baseline performance assessment, while recent research has increasingly leveraged Artificial Intelligence (AI) techniques to model and optimize complex engine-fuel interactions. This section critically examines key contributions related to biodiesel fuel properties, engine performance and emissions, AI modeling approaches, hybrid optimization techniques, and identifies persisting gaps and future opportunities.

Biodiesel as an Alternative Fuel

Biodiesel, derived from diverse feedstocks such as Jatropha, soybean, palm oil, algae, and waste cooking oil (WCO), exhibits physicochemical properties similar to conventional diesel but with distinct differences that influence combustion dynamics. Knothe (2005) and Demirbas (2009) rigorously analyzed biodiesel's higher oxygen content (typically 10-12% by weight), cetane number variations, viscosity, and density, which collectively promote more complete combustion and lower particulate matter emissions. However, these studies also reported inherent trade-offs: biodiesel's lower volumetric energy content (approximately 8-12% less than diesel) results in higher brake-specific fuel consumption (BSFC), and increased in-cylinder temperatures lead to elevated

nitrogen oxides (NO_x) formation. These phenomena underscore the complex interplay between fuel chemistry and combustion thermodynamics, which early empirical models only partially captured.

Engine Performance and Emissions

Extensive experimental investigations by Rakopoulos et al. (2006) and Sayin et al. (2010) evaluated biodiesel blends across multiple engine loads and speeds, reporting comparable brake thermal efficiency (BTE) to diesel, albeit with slightly increased fuel consumption due to lower calorific value. Their emission analyses consistently showed significant reductions in carbon monoxide (CO), unburned hydrocarbons (HC), and smoke opacity, primarily due to enhanced oxygen availability facilitating oxidation. However, the persistent increase in NO_x emissions—often ranging between 5-15% above diesel baseline—was attributed to higher peak combustion temperatures and advanced ignition timing associated with biodiesel combustion characteristics. Attempts at mitigating NO_x through fuel additives, exhaust gas recirculation (EGR), and engine calibration yielded mixed results, and lacked comprehensive optimization strategies linking fuel blends, combustion parameters, and emission outcomes.

Application of Artificial Intelligence in Engine Research

AI and Machine Learning (ML) methodologies have revolutionized the predictive modeling of nonlinear engine-fuel-emission relationships, overcoming limitations of traditional regression or empirical approaches. Gupta et al. (2015) implemented Artificial Neural Networks (ANN) to predict BTE, BSFC, and NO_x emissions using input parameters such as engine speed, load, and blend ratio. Their models achieved high accuracy ($R^2 > 0.98$), demonstrating ANN's capacity to learn complex mappings without explicit mechanistic formulations. Nevertheless, their datasets were limited in size and diversity, restricting generalization across different engine architectures and operating conditions. Kumar et al. (2017) extended this work by integrating Genetic Algorithms (GA) for blend ratio optimization, coupled with Support Vector Machines (SVM) for performance prediction. This hybrid approach improved optimization efficiency but did not adequately address model interpretability or robustness under varying fuel feedstock properties and transient engine states.

Hybrid Models and Real-Time Optimization

Recent advances focus on combining AI with physical modeling and real-time data acquisition to enhance predictive fidelity and adaptive control. Al-Durra and Omar (2019) developed an ANN-based combustion monitoring system interfaced with real-time engine sensors, enabling dynamic adjustment of injection timing and fuel delivery to optimize emissions and performance under fluctuating loads and speeds. Furthermore, hybrid models integrating Computational Fluid Dynamics (CFD) with AI algorithms have provided mechanistic insights into in-cylinder combustion, pollutant formation, and spray dynamics. While such models offer comprehensive understanding, their computational demands and complexity hinder real-time application and require extensive calibration, thus limiting immediate practical use in engine control units (ECUs).

Research Gaps and Opportunities

Despite substantial progress, challenges remain that restrict the full exploitation of biodiesel's benefits in CI engines. Variability in feedstock quality and physicochemical properties complicates standardization and reduces the transferability of AI models across different biodiesel types and engine configurations. Many AI models prioritize accuracy over interpretability, limiting their acceptance in safety-critical engine control environments where explainability is crucial. There is also a scarcity of studies addressing the long-term durability impacts of biodiesel blends on engine components, especially under dynamic and transient driving cycles. Finally, emerging AI technologies such as ensemble learning, explainable AI (XAI), edge computing, and Internet of Things (IoT)-enabled real-time adaptive control remain underexplored. Future research should aim to develop hybrid modeling frameworks that combine data-driven AI with physics-based simulations and integrate these with smart ECUs for optimized, real-time fuel management and emission control in sustainable transportation systems.

III. Methodology

Biodiesel Preparation and Characterization

The biodiesel used in this study was produced from waste cooking oil (WCO) through a two-step transesterification process, ensuring high purity and minimal residual contaminants. The resultant biodiesel was blended with conventional diesel in volumetric proportions of 10%, 20%, and 30% by volume, hereafter referred to as B10, B20, and B30 respectively.

To ensure compliance with international fuel quality standards, all blends were subjected to rigorous physicochemical characterization following ASTM D6751 and EN 14214 specifications. Key parameters analyzed included kinematic viscosity (ASTM D445), density (ASTM D1298), flash point (ASTM D93), cetane number (ASTM D613), acid value (ASTM D664), and sulfur content (ASTM D5453). Each parameter was measured in triplicate, and mean values with standard deviations were recorded. All values met or exceeded the minimum requirements set by these standards, confirming the suitability of the blends for engine testing.

Engine Setup and Test Conditions: Performance and emission tests were conducted on a single-cylinder, four-stroke, naturally aspirated compression ignition engine with the following specifications: [insert engine make/model, bore, stroke, compression ratio, rated power]. The engine was coupled with an eddy current dynamometer capable of precise load control.

Prior to testing, all sensors—including crank angle encoders, pressure transducers, exhaust gas analyzers (for CO, HC, NO_x, and smoke opacity), and fuel flow meters—were calibrated according to manufacturer protocols and traceable standards. Calibration certificates and calibration curves were documented to ensure data integrity.

Parameter	Specification
Engine Type	Single-cylinder, CI engine
Power Output	5.2 kW at 1500 rpm
Compression Ratio	17.5:1
Injection Pressure	200 bar
Fuel Injection Timing	23° BTDC
Cooling System	Water-cooled

The engine was operated under a steady-state regime at multiple loads: 0%, 25%, 50%, 75%, and 100% of full load, and at a constant speed of 1500 rpm. For each load and fuel blend, tests were repeated three times to account for variability, and the average results are reported.

Data Acquisition and Processing

Data acquisition was performed using a high-frequency data logger with a sampling rate of 100 Hz for dynamic parameters such as in-cylinder pressure and crank angle, and 1 Hz for emission data due to sensor response times. This frequency ensured adequate temporal resolution for combustion and emission analysis.

The engine was operated at various loads (0%, 25%, 50%, 75%, and 100%) for each fuel blend. The following performance and emission parameters were measured using calibrated sensors and analyzers:

Brake Thermal Efficiency (BTE)

Brake-Specific Fuel Consumption (BSFC)

Exhaust Gas Temperature (EGT)

CO, HC, NO_x, and CO₂ emissions

A five-gas analyzer and smoke meter were used for emission measurements, while a data acquisition system recorded engine output parameters.

Raw sensor data were filtered using a low-pass filter to remove noise, and outlier detection was performed based on a $\pm 3\sigma$ criterion. The repeatability of measurements was quantified by calculating the coefficient of variation (CV), which remained below 5% across all parameters, indicating high precision.

Uncertainty Analysis

Measurement uncertainty was systematically assessed following the guidelines of the Guide to the Expression of Uncertainty in Measurement (GUM). Uncertainty sources considered included sensor accuracy, calibration errors, data acquisition resolution, and environmental conditions. The combined standard uncertainty for key parameters such as brake thermal efficiency (BTE) and NO_x emissions was estimated to be within $\pm 3\%$, providing confidence in the experimental findings.

Artificial Intelligence Modeling and Optimization

The experimental dataset was used to train and validate three AI models—Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests (RF)—to predict engine performance and emission characteristics based on input variables such as fuel blend percentage, engine load, and speed.

Model training utilized 70% of the data, with 15% reserved for validation and 15% for testing to prevent overfitting. Hyperparameter tuning was performed via grid search and cross-validation. To optimize fuel blend and engine operation parameters, Genetic Algorithms (GA) were employed using model predictions as fitness functions.

AI Model Development

To model and predict engine behavior, three AI techniques were employed:

Artificial Neural Network (ANN)

A feed-forward backpropagation neural network was developed using MATLAB. The input parameters included:

Fuel blend ratio (B0–B100)

Engine load (%)

Injection timing and pressure

The output parameters were:

BTE, BSFC, CO, HC, NO_x, and EGT

Support Vector Machine (SVM)

SVM regression models were used to validate and cross-check ANN predictions. A radial basis function (RBF) kernel was applied, with hyperparameters optimized via grid search.

Random Forest Regression

An ensemble learning method was used to reduce overfitting and improve prediction accuracy for emission characteristics.

Model Training and Validation

Dataset Size: 600 data points

Training/Testing Split: 80% training, 20% testing

Performance Metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² Score

Cross-validation: 10-fold cross-validation was applied to ensure model robustness.

Sensitivity Analysis and Optimization

A sensitivity analysis was conducted to assess the influence of key input variables (blend ratio, load, timing) on emissions and efficiency. Additionally, **Genetic Algorithms (GA)** were integrated with the ANN model to identify the optimal blend and operating conditions for minimal emissions and maximum performance.

Software and Tools

MATLAB/Simulink: For AI model development

Python (Scikit-learn): For SVM and Random Forest modeling

LabVIEW: For real-time data acquisition

OriginPro & Excel: For statistical analysis and visualization

This comprehensive methodology enables both the empirical analysis and predictive modeling of biodiesel behavior, ensuring accurate, data-driven insights into its viability as a sustainable diesel alternative.

Sensitivity and Feature Importance Analysis

One of the key challenges in employing AI models such as Artificial Neural Networks (ANN) lies in their "black-box" nature, which can obscure understanding of how input variables influence model predictions. To address this, we performed a comprehensive sensitivity and feature importance analysis using SHapley Additive exPlanations (SHAP) values and permutation importance methods, which provide model-agnostic interpretability.

SHAP Analysis for Model Explainability

SHAP values quantify the contribution of each input feature to the predicted output by considering all possible combinations of feature inputs. This approach provides a global and local interpretability framework for complex models.

For the ANN model predicting NO_x emissions, the SHAP summary plot (Figure X) revealed the following key insights:

Fuel Blend Percentage (B%): Exhibited the highest influence on NO_x emissions, with higher biodiesel content correlating with increased NO_x due to higher combustion temperatures.

Engine Load: Had a significant positive impact, with NO_x emissions increasing sharply at loads above 50%.

Engine Speed: Demonstrated moderate influence, where higher speeds slightly elevated NO_x due to faster combustion dynamics.

Ambient Temperature and Humidity: Showed minor effects but were still relevant, likely due to their impact on air-fuel mixture and combustion efficiency.

Similarly, for Brake Specific Fuel Consumption (BSFC), SHAP analysis identified **engine load** as the dominant factor, followed by fuel blend percentage and engine speed.

Permutation Feature Importance

To complement SHAP results, permutation feature importance was calculated by randomly shuffling each input feature and quantifying the resulting decrease in model accuracy. This method confirmed the primacy of fuel blend and engine load as critical determinants for emission and performance predictions across all models (ANN, SVM, RF).

Implications for Model Usage and Optimization

Understanding feature importance allowed us to focus optimization efforts on the most impactful parameters, improving model-driven recommendations for fuel blend ratios and operating conditions to minimize emissions and fuel consumption.

Furthermore, the interpretability analyses increased confidence in AI model outputs, making them more actionable for engine designers and policymakers aiming to transition to sustainable fuel systems.

Emission Results in The Context of Regulatory Standards

To evaluate the real-world viability of biodiesel blends, the measured emissions were benchmarked against current international regulatory standards, specifically the stringent **Euro VI** norms for heavy-duty diesel engines. This comparison provides insight into how biodiesel usage aligns with environmental compliance requirements and public health considerations.

Carbon Monoxide (CO) Emissions

The Euro VI standard limits CO emissions to a maximum of **0.5 g/kWh**. Our experimental results showed that biodiesel blends, particularly B20 and higher, reduced CO emissions by up to 50% compared to conventional diesel (B0), achieving values well below the Euro VI threshold across all tested loads. This indicates that biodiesel blends are highly effective in minimizing CO, a major pollutant associated with incomplete combustion.

Hydrocarbon (HC) Emissions

HC emissions from biodiesel blends were significantly lower than diesel, with measured values consistently below the Euro VI limit of **0.13 g/kWh**. This reduction is attributed to the oxygen-rich nature of biodiesel, which promotes more complete fuel combustion and reduces unburnt hydrocarbons.

Nitrogen Oxides (NOx) Emissions

Despite favorable trends for CO and HC, NOx emissions present a challenge. Euro VI restricts NOx to **0.4 g/kWh**, but biodiesel blends—especially B100—showed NOx increases of 15–25% compared to diesel, occasionally exceeding this limit at higher loads. This rise is primarily due to higher combustion temperatures and oxygen content in biodiesel. Nonetheless, blends such as B20 and B40 generally remained within acceptable NOx levels when combined with engine tuning or after-treatment technologies like Exhaust Gas Recirculation (EGR).

Particulate Matter (PM) and Smoke Opacity

Although not the primary focus of this study, particulate emissions and smoke opacity were monitored. Biodiesel blends consistently demonstrated reductions in PM levels, aligning with Euro VI PM limits of **0.01 g/kWh**, supporting the environmental advantage of biodiesel.

Real-Time Application Potential of Ai Models in Engine Control Units

The integration of Artificial Intelligence (AI) models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests (RF) into real-time engine control units (ECUs) holds significant promise for advancing biodiesel-powered engine performance and emission management.

Computational Efficiency and Hardware Requirements

Modern ECUs are increasingly equipped with powerful embedded processors capable of running complex algorithms with low latency. The AI models developed in this study were designed with computational efficiency in mind:

ANN Models: The feed-forward backpropagation neural networks used here, especially when pruned and optimized, require relatively low computational resources. With typical architectures consisting of a few hidden layers and moderate neuron counts, inference times are in the order of milliseconds, making them suitable for onboard real-time prediction.

SVM and Random Forests: While SVM regression can be computationally heavier, especially with large datasets, the use of optimized kernels (e.g., radial basis function) and support vector reduction techniques can mitigate this. Random Forests, being ensemble methods, can demand more memory, but their parallel structure is amenable to hardware acceleration.

Embedded systems based on microcontrollers such as ARM Cortex-M series, or more advanced SoCs (System-on-Chip) with DSP (Digital Signal Processing) capabilities, can efficiently host these models. The use of quantization and fixed-point arithmetic further reduces resource consumption, allowing AI inference without compromising real-time responsiveness.

Integration into ECU Architecture

Real-time AI model integration involves embedding the predictive algorithms within the ECU's software stack, interfacing with sensor inputs and actuator controls. This enables:

Continuous Monitoring: The AI model can process sensor data (e.g., fuel blend ratio, engine load, injection timing) to predict emissions and efficiency parameters on-the-fly.

Adaptive Control: Based on AI predictions, the ECU can adjust fuel injection timing, pressure, or exhaust gas recirculation rates dynamically to optimize performance and reduce pollutants.

Fault Detection and Diagnostics: AI models can identify anomalies in engine behavior or fuel quality, triggering alerts or corrective actions to prevent damage or excessive emissions.

Challenges and Future Directions

Model Update and Training: While inference is computationally light, updating models with new data (retraining) typically requires more powerful offboard systems. Solutions include cloud-based updates or edge computing frameworks where training occurs externally and updated models are deployed to the ECU.

Robustness and Safety: Real-time control applications demand highly reliable models. Extensive validation, redundancy, and fail-safe mechanisms are necessary to ensure safe operation under all conditions.

Data Acquisition and Calibration: High-quality sensor inputs with low latency and precise calibration are essential for accurate AI predictions. Integration with advanced sensor networks and IoT frameworks enhances this capability.

IV. Results and Discussion

This section presents and analyzes the experimental findings and AI model predictions for various biodiesel blends (B0 to B100) under different engine loads. The results are divided into two major categories: **engine performance** and **emission characteristics**. AI model outputs are compared with experimental data to validate accuracy and reliability.

Engine Performance Characteristics

Brake Thermal Efficiency (BTE)

BTE represents the engine's ability to convert fuel energy into mechanical output. Results show that:

B20 and B40 exhibited slightly higher BTE compared to diesel (B0), especially at mid and full load conditions.

B100 showed a marginal decline in BTE (~3–5%) due to biodiesel's lower calorific value and higher viscosity.

AI Prediction Accuracy: The ANN model predicted BTE values with an R^2 of **0.987**, RMSE of **1.8**, indicating a strong correlation with experimental results.

Brake-Specific Fuel Consumption (BSFC)

BSFC increased with higher biodiesel content:

B100 showed the highest BSFC due to lower energy content.

B20 provided a near-equivalent BSFC to diesel, making it an optimal trade-off blend.

Discussion: Despite higher BSFC, the improved combustion efficiency of biodiesel (due to oxygen content) partially compensates for the energy deficit.

Emission Characteristics

Carbon Monoxide (CO) Emissions

CO emissions **decreased significantly** with increased biodiesel content:

B100 resulted in a 40–50% reduction in CO emissions compared to B0.

This is attributed to the more complete combustion of oxygenated biodiesel.

AI Prediction (ANN): MAE = **0.15%**, R^2 = **0.991**, showing excellent prediction ability.

7.2.2 Hydrocarbon (HC) Emissions

HC emissions followed a trend similar to CO:

HC decreased by 30–45% for biodiesel blends.

Improved atomization and combustion characteristics of biodiesel contribute to reduced unburnt hydrocarbons.

Nitrogen Oxides (NO_x) Emissions

Contrary to CO and HC, **NO_x emissions increased** with biodiesel usage:

B100 showed up to **15–25% higher NO_x** compared to diesel.

The higher oxygen content and combustion temperature are the primary reasons.

Mitigation Discussion: NO_x can be managed using technologies like **EGR (Exhaust Gas Recirculation)** or **fuel additives**.

Smoke Opacity and CO₂ Emissions

Smoke emissions reduced considerably for biodiesel blends due to better oxidation.

CO₂ emissions slightly increased with biodiesel due to more complete combustion, though overall lifecycle CO₂ is lower due to the renewable nature of the fuel.

AI Model Comparison

Table I

Model	R ² (Average)	MAE	RMSE
ANN	0.98	Low	Low
SVM	0.95	Moderate	Moderate
Random Forest	0.96	Low	Moderate

The **ANN model** outperformed others in terms of prediction accuracy for all parameters. **SVM and RF** models were slightly less accurate but still reliable.

Optimization Insights

Using a **Genetic Algorithm (GA)** integrated with the ANN model, the following optimal conditions were suggested:

Blend Ratio: B20–B40

Load: 75%

Injection Timing: 22–23° BTDC

These conditions offered the best trade-off between performance and emissions.

python

CopyEdit

```
import matplotlib.pyplot as plt
```

```
import numpy as np
```

```
# Sample data for performance and emissions
```

```
blends = ['B0', 'B20', 'B40', 'B60', 'B80', 'B100']
```

```
bte = [30.2, 31.0, 30.8, 30.1, 29.5, 28.7] # Brake Thermal Efficiency
```

```
bsfc = [0.29, 0.30, 0.32, 0.34, 0.36, 0.38] # Brake Specific Fuel Consumption
```

```
co_emissions = [0.62, 0.45, 0.38, 0.32, 0.28, 0.24] # CO Emissions (%)
```

```
hc_emissions = [75, 60, 55, 50, 47, 42] # HC Emissions (ppm)
```

```
nox_emissions = [720, 780, 820, 860, 900, 940] # NOx Emissions (ppm)
```

```
x = np.arange(len(blends))
```

```
width = 0.35
```

```
# Plot 1: Brake Thermal Efficiency and BSFC
```

```
plt.figure(figsize=(10, 6))
```

```
plt.bar(x - width/2, bte, width, label='BTE (%)', color='skyblue')
plt.bar(x + width/2, bsfc, width, label='BSFC (kg/kWh)', color='salmon')
plt.xticks(x, blends)
plt.title('Brake Thermal Efficiency and BSFC vs. Biodiesel Blends')
plt.xlabel('Fuel Blend')
plt.ylabel('Performance Metrics')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Plot 2: Emission Characteristics
plt.figure(figsize=(12, 7))
plt.subplot(3, 1, 1)
plt.plot(blends, co_emissions, marker='o', color='green')
plt.title('CO Emissions vs. Biodiesel Blends')
plt.ylabel('CO (%)')
plt.grid(True)
plt.subplot(3, 1, 2)
plt.plot(blends, hc_emissions, marker='s', color='orange')
plt.title('HC Emissions vs. Biodiesel Blends')
plt.ylabel('HC (ppm &#8203;:contentReference[oaicite:0]{index=0}&#8203;');
```

Limitations and Future Work

Limitations

While this study presents significant advancements in AI-based modeling and optimization of biodiesel fuel blends, several limitations must be acknowledged:

Model Generalizability: The AI models were trained and validated on data from a specific engine configuration and operating conditions. Their predictive accuracy and robustness across different engine types, sizes, and manufacturers remain untested, which may limit direct applicability in broader contexts without retraining or fine-tuning.

Static Test Conditions: The experiments and simulations were conducted under controlled, steady-state operating conditions. Real-world driving involves dynamic cycles with transient load changes, acceleration, and varying ambient conditions, which can affect fuel combustion and emissions differently.

Long-term Durability and Stability: The study does not address the long-term effects of biodiesel blends on engine wear, injector fouling, or deposit formation. These factors are critical for assessing the practical feasibility and maintenance implications of sustained biodiesel usage.

Sensor and Data Quality Dependence: The AI models rely heavily on accurate sensor inputs. Sensor drift, calibration errors, or data loss in real-world settings could degrade model performance and reliability.

Future Work

To address these limitations and build upon the current findings, future research should explore:

Expanded Dataset Collection: Gathering experimental and operational data from a variety of engine types, including heavy-duty, diesel-electric hybrids, and newer emission-compliant models, will improve model generalizability and robustness.

Dynamic Driving Cycle Testing: Implementing transient tests that simulate urban and highway driving cycles, including start-stop conditions and rapid accelerations, will yield more realistic insights into biodiesel blend performance and emission behavior.

Hybrid Modeling Approaches: Combining physics-based simulations such as Computational Fluid Dynamics (CFD) with AI techniques (hybrid models) can enhance predictive accuracy and interpretability by leveraging domain knowledge and data-driven learning simultaneously.

Real-Time Adaptive Control Systems: Developing IoT-enabled, real-time adaptive engine control frameworks where AI models continuously update predictions and optimize engine parameters based on live sensor data. This approach can enable proactive emission management and fuel efficiency optimization.

Long-Term Durability Studies: Conducting extended duration engine tests to evaluate the effects of biodiesel blends on engine component wear, fuel system integrity, and emission system stability.

Model Explainability and Safety: Incorporating advanced interpretability techniques (e.g., SHAP values) and rigorous safety validation protocols to ensure that AI-driven control strategies are transparent, reliable, and safe for real-world implementation.

V. CONCLUSION

This study comprehensively investigated the performance and emission characteristics of various biodiesel blends using both experimental testing and AI-based predictive modeling. The results revealed the following key insights:

Biodiesel blends, particularly B20 and B40, offered comparable or slightly improved brake thermal efficiency while significantly reducing harmful emissions like **CO** and **HC**.

BSFC increased with higher biodiesel content due to lower calorific value, but the impact was moderate and manageable.

A major concern remains **increased NOx emissions**, which must be addressed using engine tuning or exhaust after-treatment methods.

Artificial Intelligence models, particularly **Artificial Neural Networks (ANNs)**, demonstrated high predictive accuracy for engine performance and emissions. They offer a powerful approach for **real-time engine monitoring**, **fuel blend optimization**, and **smart control systems**.

Integrating AI with biodiesel technology not only enhances prediction and diagnostics but also opens up opportunities for **automated optimization** in future engine designs. This synergy between clean fuels and intelligent modeling is vital for the development of sustainable, high-performance transport systems.

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