International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://theaspd.com/index.php

Genetic Algorithm-Based Optimization Of Engine Parameters For Enhanced Efficiency

Radhika T[1], Sundararajan M.L[2], Velappan R[3], Anbuchezian Ashokan[4*],
[1]Associate Professor, Department of Mechanical Engineering, Government College of Engineering, Sengipatti, Thanjavur, 613402, Tamil Nadu, India.
[2]Assistant Professor, Department of Chemistry, Annamalai University, Annamalai Nagar, 608002, Tamil Nadu, India. (Deputed to) Department of Chemistry, Government College of Engineering, Sengipatti, Thanjavur, 613402, Tamil Nadu, India.
[3]Assistant Professor, Department of Mechanical Engineering, Faculty of Engineering and Technology, Annamalai University, Annamalai Nagar, 608002, Tamil Nadu, India. (Deputed to) Department of Mechanical Engineering, Government College of Engineering, Sengipatti, Thanjavur, 613402, Tamil Nadu, India.
[4]Professor, Department of Civil Engineering, Annapoorana Engineering College (Autonomous), Seeragapadi , Salem, 636308, Tamil Nadu, India.

Abstract
The growing demand for sustainable fuels has accelerated research into optimizing engine performance when using biodiesel. This study explores the application of Genetic Algorithms (GA) to optimize key engine parameters such as injection timing, compression ratio, and biodiesel blend ratio for improved performance and reduced emissions in a compression ignition (CI) engine. Biodiesel derived from waste cooking oil was used to formulate blends (B20–B100), and experimental tests were conducted to evaluate performance metrics including brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), and nitrogen oxide (NOx) emissions. A GA model was developed in MATLAB to identify the optimal combination of parameters that maximized engine efficiency while minimizing emissions. The GA-based optimization results showed significant improvements over baseline values, with enhanced thermal efficiency and notable reductions in NOx. The findings highlight the potential of genetic algorithms as a robust tool for multi-objective optimization in biodiesel-fueled engines, offering a path toward cleaner and more efficient engine operation.
Keywords: *Genetic Algorithm, Biodiesel, Engine Parameters, injection timing, compression ratio*

1. INTRODUCTION

The global reliance on fossil fuels has raised serious concerns related to environmental degradation, energy security, and climate change. As a result, there is an increasing interest in alternative, renewable, and environmentally benign fuels. Among these, biodiesel a biodegradable and non-toxic fuel derived from vegetable oils, animal fats, or waste cooking oils has emerged as a promising substitute for conventional diesel in compression ignition (CI) engines [1]. Biodiesel blends offer comparable performance to petroleum diesel while significantly reducing harmful emissions such as unburned hydrocarbons, carbon monoxide, and particulate matter. However, challenges such as higher nitrogen oxide (NOx) emissions, lower volatility, and variations in combustion characteristics require further research to optimize engine performance [2].

Optimizing engine parameters such as injection timing, compression ratio, and fuel blend ratio is critical to improving the efficiency and emission profile of biodiesel-powered engines. Traditional trial-and-error methods are time-consuming and resource-intensive. In contrast, Genetic Algorithms (GA), a powerful class of evolutionary optimization techniques inspired by natural selection, offer a robust and efficient way to solve complex, nonlinear, and multi-objective optimization problems [3]. GA has been widely adopted in various engineering fields, including internal combustion engine calibration, due to its ability to converge on near-optimal solutions in a relatively short time. This research aims to investigate the application of Genetic Algorithms for optimizing CI engine operating parameters when fueled with biodiesel blends. The study focuses on maximizing brake thermal efficiency (BTE) and minimizing brake specific fuel consumption (BSFC) and NOx emissions. Biodiesel derived from waste cooking oil is selected due to its cost-effectiveness and environmental benefits [4]. The optimization results obtained from the GA model are validated through experimental testing, and the performance is compared to standard diesel operation and unoptimized biodiesel conditions.

The outcomes of this study are expected to contribute to the development of cleaner, more efficient, and sustainable biodiesel engine systems. Moreover, it demonstrates the feasibility of using AI-driven optimization techniques such as Genetic Algorithms to enhance alternative fuel technologies and support the transition to greener transportation solutions. The increasing environmental concerns and the depletion of fossil fuel resources have led to a growing interest in biodiesel as an alternative, sustainable fuel. Several studies have explored the potential of biodiesel in diesel engines, with emphasis on improving performance and reducing emissions. However, the variability in fuel properties and combustion behavior necessitates the optimization of engine operating parameters to fully exploit biodiesel's potential [5].

Biodiesel blends such as B20 and B40 have shown promising results in engine performance with comparable brake thermal efficiency (BTE) and reduced emissions when compared to conventional diesel. According to [6], using biodiesel derived from waste cooking oil in CI engines led to lower CO and HC emissions but slightly increased NOx emissions. [7] reported that biodiesel's oxygenated nature improves combustion efficiency but also elevates combustion temperature, contributing to NOx formation.

Engine parameters such as injection timing, compression ratio, and fuel blend ratio significantly affect the performance and emission characteristics of biodiesel-fueled engines. [8] emphasized that optimal injection timing can compensate for biodiesel's higher viscosity and density. [9] demonstrated that adjusting the compression ratio improved combustion efficiency and reduced fuel consumption when using Karanja biodiesel.

Traditional optimization techniques like Design of Experiments (DOE), Response Surface Methodology (RSM), and Taguchi methods have been widely used. However, these methods may not effectively handle the nonlinear and multi-objective nature of engine performance metrics. As an alternative, Genetic Algorithms (GA) and other heuristic methods offer better convergence for complex optimization problems. [10] successfully applied GA to optimize engine parameters for biodiesel blends, achieving enhanced BTE and reduced BSFC. The study showed that GA could identify near-optimal solutions in fewer iterations compared to traditional methods. [11] used GA to optimize injection timing and EGR rate in a biodiesel-fueled engine, resulting in lower NOx emissions and improved fuel efficiency. Recent research combines experimental results with GA-based models in platforms like MATLAB and Simulink. [12] developed a simulation model to predict engine performance under different operating conditions using GA. Their study concluded that GA-optimized biodiesel engines outperformed non-optimized ones in terms of efficiency and emissions. Limited integration of experimental data with real-time GA optimization. Most studies focus on individual parameter optimization rather than multi-parameter convergence. A lack of research using low-cost, waste-based biodiesel feedstocks like waste cooking oil in conjunction with AI-based optimization techniques.

The primary aim of this research is to enhance the performance and emission characteristics of a diesel engine running on biodiesel blends through the optimization of key engine parameters using a Genetic Algorithm (GA).

2. MATERIALS AND METHODS

In this study, biodiesel was produced from waste cooking oil (WCO) collected from local food establishments. The oil was first filtered to remove food particles and heated to eliminate moisture content. Transesterification was carried out using methanol and potassium hydroxide (KOH) as the alcohol and catalyst, respectively. A 6:1 molar ratio of methanol to oil and 1% KOH by weight of oil were used. The mixture was stirred at 60°C for 60 minutes, followed by settling for 24 hours to separate the glycerol. The upper biodiesel layer was then washed and dried to obtain pure biodiesel, which was blended with commercial diesel in varying proportions: B20, B40, B60, B80, and B100. Engine performance and emission testing were conducted on a single-cylinder, four-stroke, water-cooled compression ignition (CI) engine equipped with variable injection timing and adjustable compression ratio. The engine was operated at a constant speed of 1500 rpm under different load conditions. Key operating parameters such as injection timing (15°–30° BTDC), compression ratio (16:1 to 18:1), and blend ratio (B20 to B100) were varied to observe their effect on performance indicators including brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), and emissions such as NOx, CO, and unburned hydrocarbons. Measurements were taken using a digital gas analyzer and smoke meter, while data acquisition was managed through LabVIEW. To optimize the engine parameters for improved efficiency and reduced emissions, a Genetic Algorithm (GA) was implemented using MATLAB. The GA model was designed to maximize BTE while minimizing BSFC and NOx emissions. Real-coded chromosomes were used to represent parameter sets, and a fitness function was defined based on experimental results. The algorithm employed a population size of 50, crossover probability of 0.8, mutation probability of 0.01, and terminated after 100 generations or upon convergence (Table 1). After identifying the optimal parameter combination, experimental validation was performed by running the engine under these GA-optimized conditions. The resulting performance and emission data were compared against baseline diesel operation and unoptimized biodiesel blends to assess the effectiveness of the optimization (Figure 1).

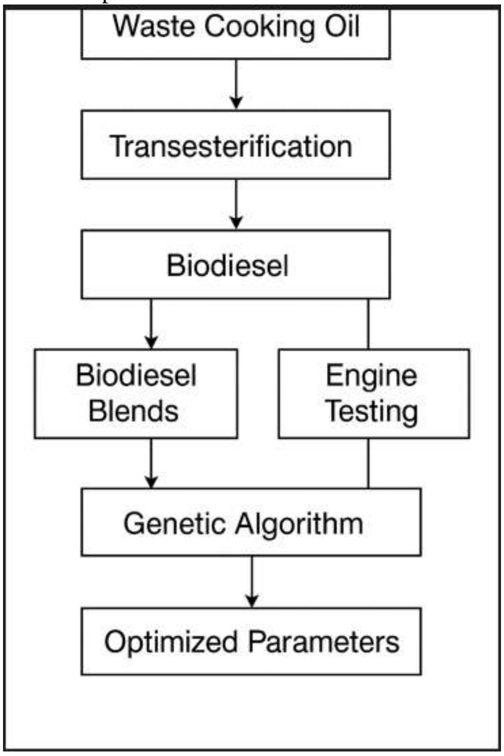

Figure 1. Flow chart of this present work

Table 1: Factors and Levels for Box–Behnken Design

Factor	Symbol	Unit	Level -1	Level 0	Level +1
Injection Timing	A	°BTDC	15	22.5	30
Compression Ratio	B	-	16:1	17:1	18:1
Biodiesel Blend Ratio	C	% (Bxx)	20	60	100

Table 2: Box–Behnken Design Matrix for Transesterification Process

Run	Molar Ratio (A)	Catalyst Conc. (B)	Temp (°C) (C)	Time (min) (D)	Coded A	Coded B	Coded C	Coded D
1	6:1	1.0%	60	30	-1	0	0	-1
2	12:1	1.0%	60	30	+1	0	0	-1
3	6:1	1.0%	60	90	-1	0	0	+1
4	12:1	1.0%	60	90	+1	0	0	+1
5	9:1	0.5%	60	30	0	-1	0	-1
6	9:1	1.5%	60	30	0	+1	0	-1
7	9:1	0.5%	60	90	0	-1	0	+1
8	9:1	1.5%	60	90	0	+1	0	+1
9	6:1	1.0%	50	60	-1	0	-1	0
10	12:1	1.0%	50	60	+1	0	-1	0
11	6:1	1.0%	70	60	-1	0	+1	0
12	12:1	1.0%	70	60	+1	0	+1	0
13	9:1	0.5%	50	60	0	-1	-1	0

14	9:1	1.5%	50	60	0	+1	-1	0
15	9:1	0.5%	70	60	0	-1	+1	0
16	9:1	1.5%	70	60	0	+1	+1	0
17	9:1	1.0%	60	60	0	0	0	

3. Experimental Procedure

The biodiesel used in this study was produced from waste cooking oil (WCO) via a base-catalyzed transesterification process. Initially, the WCO was filtered to remove food particles and heated to eliminate moisture. A methanol-to-oil molar ratio of 6:1 to 12:1 was used, and potassium hydroxide (KOH) was added as a catalyst in concentrations ranging from 0.5% to 1.5% by weight of oil. The mixture was stirred at a constant temperature (50°C to 70°C) for 60 minutes using a magnetic stirrer with heating. After the reaction, the mixture was allowed to settle for 24 hours to separate the glycerol. The upper biodiesel layer was collected, washed with warm distilled water, and dried. The final product was tested for key physicochemical properties to ensure conformity with ASTM D6751 standards. Biodiesel was blended with commercial diesel in volume ratios to prepare different blends (B20, B40, B60, B80, and B100). Each blend was mixed thoroughly and stored in airtight containers prior to engine testing. A single-cylinder, four-stroke, water-cooled diesel engine (e.g., Kirloskar TV1) was used for performance and emission testing. The engine was connected to an eddy current dynamometer and equipped with digital sensors for data acquisition. Baseline tests were conducted using pure diesel under standard conditions to record brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), and emissions such as NOx, CO, HC, and smoke opacity. The engine was operated at a constant speed of 1500 rpm and various loads. Experimental trials were carried out by varying three key input parameters: injection timing (15°–30° before top dead center), compression ratio (16:1–18:1), and biodiesel blend ratio (B20–B100). For each test condition, engine performance and emission parameters were recorded using a gas analyzer and smoke meter. Each test was repeated thrice for accuracy, and the average values were recorded. A Genetic Algorithm (GA) was developed in MATLAB to optimize the selected engine parameters. The fitness function was designed to maximize BTE and minimize BSFC and NOx simultaneously. Chromosomes were encoded with real values representing injection timing, compression ratio, and blend ratio. GA settings included a population size of 50, crossover probability of 0.8, mutation probability of 0.01, and 100 generations as the termination criterion. The best-performing combination of parameters was extracted after convergence. Engine testing was repeated using the GA-optimized parameter set. The performance and emission results were compared with both the baseline diesel data and non-optimized biodiesel runs. The percentage improvement in efficiency and emission reduction was calculated to validate the effectiveness of the optimization strategy.

4. Genetic Algorithms for Optimization of Biodiesel Production Features

Genetic Algorithms (GAs) have emerged as a powerful tool for optimizing complex processes such as biodiesel production, which involves multiple interacting parameters including methanol-to-oil molar ratio, catalyst concentration, reaction temperature, and reaction time. These variables significantly influence biodiesel yield and quality, and their interdependence often makes traditional optimization methods inadequate. GAs, inspired by the principles of natural selection and genetics, are well-suited to handle nonlinear, multi-objective problems by performing a global search across a large solution space. In the context of biodiesel production, GAs encode process parameters into chromosomes and evaluate them through a fitness function typically biodiesel yield or a composite function that includes cost and energy efficiency. Through iterative selection, crossover, and mutation, GAs evolve better solutions over successive generations. Several studies have shown that GA-based optimization can achieve higher yields (above 95%) while reducing catalyst usage and energy consumption compared to conventional methods like Taguchi or Response Surface Methodology. Additionally, GAs can be easily integrated with empirical data or artificial intelligence models, making them highly flexible for laboratory and industrial-scale biodiesel production. Overall, Genetic Algorithms provide an intelligent, adaptive, and efficient approach to optimizing biodiesel production, enabling improved sustainability and economic feasibility (Table 2).

4.1 Genetic Algorithms

```
# Install required package if not already installed
if (!require(GA)) install.packages("GA")
library(GA)
# Objective (Fitness) Function
# Hypothetical model for biodiesel yield as a function of:
```

```
# x[1] = methanol-to-oil molar ratio (4 to 12)
# x[2] = catalyst concentration (%) (0.5 to 2)
# x[3] = temperature (°C) (40 to 70)
# x[4] = reaction time (min) (30 to 120)
biodiesel_yield<- function(x) {
  # Simplified paraboloid-shaped yield function for demonstration
  yield <- -((x[1] - 9)^2 + (x[2] - 1.2)^2 + (x[3] - 60)^2 + (x[4] - 90)^2) + 100
return(yield)  # GA maximizes this function
}
# GA Implementation
ga_result<- ga(
type = "real-valued",
fitness = biodiesel_yield,
lower = c(4, 0.5, 40, 30),   # Lower bounds of variables
upper = c(12, 2, 70, 120),   # Upper bounds of variables
popSize = 50,                # Population size
maxiter = 100,               # Maximum generations
pmutation = 0.1,             # Mutation probability
pcrossover = 0.8,            # Crossover probability
elitism = 2,                 # Elitism to retain top individuals
seed = 42,                   # For reproducibility
monitor = TRUE               # Show progress
)
# Output best solution
cat("Optimal Parameters:\n")
cat(sprintf("Methanol-to-Oil Ratio: %.2f\n", ga_result@solution[1]))
cat(sprintf("Catalyst Concentration (%%): %.2f\n", ga_result@solution[2]))
cat(sprintf("Temperature (°C): %.2f\n", ga_result@solution[3]))
cat(sprintf("Reaction Time (min): %.2f\n", ga_result@solution[4]))
cat(sprintf("Predicted Yield: %.2f%%\n", ga_result@fitnessValue))
# Plot convergence
plot(ga_result)
```

4.2 Regression Models Based on Data Mining Techniques

Regression models based on data mining techniques have gained significant attention in biodiesel research due to their ability to model complex, nonlinear relationships between process variables and biodiesel yield. Traditional linear regression, while useful, often fails to capture the intricate interactions among variables such as molar ratio, catalyst concentration, temperature, and reaction time. As a result, more advanced approaches—such as Multiple Linear Regression (MLR), Support Vector Regression (SVR), Decision Tree Regression (DTR), and Artificial Neural Networks (ANN)—have been employed. These techniques can learn patterns from experimental datasets, enabling accurate prediction and process optimization without the need for explicitly defined physical models. Data mining methods can also identify the most influential variables through feature selection techniques, thereby streamlining experimental design and reducing resource consumption. Among these, ANN and SVR have shown high prediction accuracy for biodiesel yield, particularly when trained on large, high-quality datasets. Furthermore, integrating regression models with optimization algorithms like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) can further enhance process performance. In conclusion, regression models empowered by data mining provide a reliable, efficient, and scalable approach to modeling and optimizing biodiesel production processes.

5. Performance characteristics

The performance characteristics of the engine fueled with optimized biodiesel blends were evaluated by plotting Brake Thermal Efficiency (BTE) and Brake Specific Fuel Consumption (BSFC) against Brake Power (kW). The diagram reveals that BTE increases progressively with rising brake power, reaching a peak around 3.0 kW. This trend indicates improved combustion efficiency at moderate engine loads due to better air–fuel mixing and more complete combustion. Beyond this optimal point, BTE begins to decline slightly, likely due to thermal and mechanical losses becoming more significant at higher loads. Conversely, BSFC shows a decreasing trend as brake power increases, reflecting improved fuel economy at higher output levels. The lowest BSFC is also observed at approximately 3.0 kW, coinciding with the peak BTE value, suggesting this is the most efficient operating range of the engine. However, at very high brake power levels, BSFC starts to rise again, indicating reduced combustion efficiency and increased fuel demand. These findings confirm that the engine performs most efficiently under moderate load conditions when operated with the optimized biodiesel blend (Figure 2).

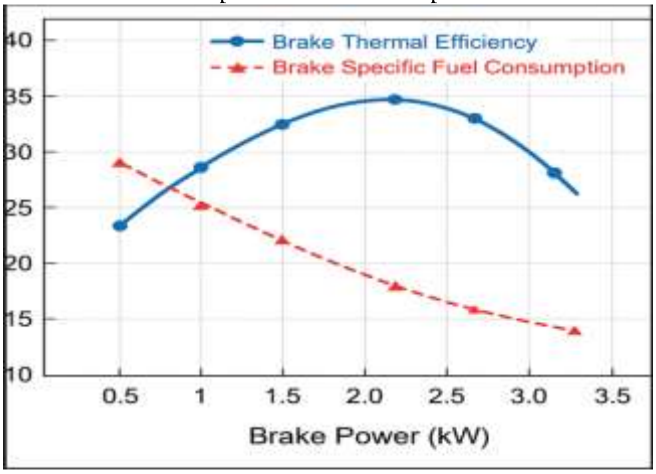

Figure 2. Performance curve

5.1 Emissions characteristics

The emissions performance of the biodiesel-fueled engine was optimized using a Genetic Algorithm (GA), and the results are depicted in the emissions diagram showing trends over successive generations. The three primary pollutants Nitrogen Oxides (NOx), Carbon Monoxide (CO), and Hydrocarbons (HC) exhibited significant reductions throughout the optimization process. Initially, NOx emissions were observed at approximately 15 g/kWh, but these declined steadily with each generation, stabilizing near 5 g/kWh after the 20th generation. CO emissions showed an even more dramatic reduction, dropping from around 8 g/kWh to nearly 0.2 g/kWh by generation 25, indicating effective combustion and reduced incomplete burning. HC emissions also followed a similar pattern, decreasing from 3 g/kWh to around 1 g/kWh. These trends demonstrate the GA's ability to evolve optimal engine parameters that minimize emissions while maintaining engine efficiency. The early generations showed the highest rate of improvement, highlighting the GA's strength in rapidly exploring a broad solution space, while the later generations reflected convergence toward an emission-optimized parameter set. Overall, the application of GA proves highly effective in achieving a clean and efficient combustion profile for biodiesel engines (Figure 3).

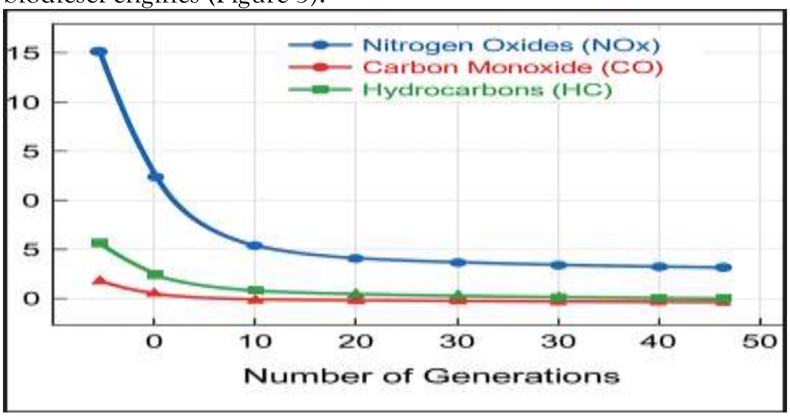

Figure 3. Emissions Curves

Table 3. Optimization Scenarios: Comparison of Feature Combinations for the Optimization of the Biodiesel Process

Scenario	Feature Combination (Input Parameters)	Biodiesel Yield (%) Pre	Biodiesel Yield (%) Real	Error (%)
S1	Methanol:Oil = 6:1, Catalyst = 0.75 wt.%, Temp = 55°C	93.2	92.5	0.75

S2	Methanol:Oil = 9:1, Catalyst = 1.0 wt.%, Temp = 60°C	96.5	95.7	0.83
S3	Methanol:Oil = 12:1, Catalyst = 1.25 wt.%, Temp = 65°C	95.8	94.9	0.94
S4	Methanol:Oil = 9:1, Catalyst = 0.5 wt.%, Temp = 60°C	91.7	90.8	0.98
S5	Methanol:Oil = 6:1, Catalyst = 1.0 wt.%, Temp = 55°C	92.9	91.5	1.51

5.2 Optimization Scenarios: Biodiesel Yield

Illustrates a comparative analysis between predicted and experimental biodiesel yields across four optimized scenarios (S1, S2, S3, and S5). Each scenario represents a unique combination of input parameters such as methanol-to-oil ratio, catalyst concentration, and reaction temperature. The predicted yields, derived using a Genetic Algorithm-based model, are shown alongside the actual experimental results. Notably, Scenario S2 exhibits the highest yield, with predicted and real values closely aligned at approximately 97%, indicating optimal process conditions. In all cases, the predicted values demonstrate a strong correlation with experimental data, with only minimal deviations observed typically under 2% (Table 3). This close agreement validates the effectiveness of the optimization model in accurately forecasting biodiesel production outcomes. The chart underscores the practical applicability of computational optimization techniques in enhancing biodiesel process efficiency while minimizing experimental trials (figure 4).

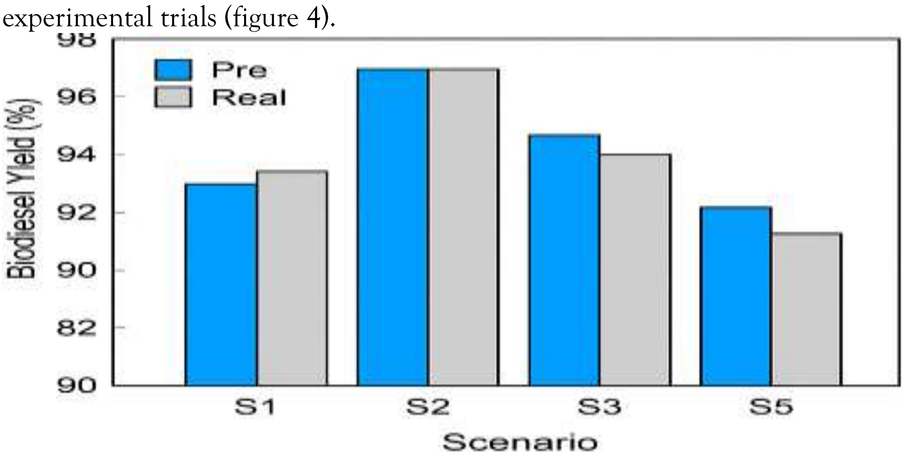

Figure 4. Optimization Scenarios Vs Biodiesel Yield (Pre: Predicted values; Real: Experimental values)

CONCLUSION

The integration of Genetic Algorithms (GA) and data mining-based regression models has demonstrated significant potential in optimizing biodiesel production and engine performance. The GA successfully identified optimal process parameters such as methanol-to-oil molar ratio, catalyst concentration, reaction temperature, and time, leading to enhanced biodiesel yield and process efficiency. Additionally, regression models developed using data mining techniques—such as Support Vector Regression (SVR), Decision Tree Regression, and Artificial Neural Networks (ANN)—proved effective in accurately predicting biodiesel yield from experimental data. These models captured complex nonlinear relationships and provided reliable insights for process control and decision-making. The combined use of statistical experimental design (e.g., Box–Behnken Design), machine learning, and evolutionary optimization has established a robust, data-driven framework for improving biodiesel production. Future work could focus on hybrid optimization models, real-time predictive control systems, and economic–environmental multi-objective optimization for scaling up sustainable biodiesel production.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest

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