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Data-Driven Modeling And Optimization Of Engine Performance Fueled By Karanja Biodiesel: A Comparative Approach

Rashid Khan[1], Brahma Nand Agrawal[2], Sudhir Kumar Singh[3]
[1,3]Department of Mechanical Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India
[2]Department of Mechanical Engineering, MRIIRS, Faridabad, Haryana, India

Abstract
The increasing demand for sustainable fuels has prompted the exploration of biodiesel as a viable alternative to conventional diesel. Karanja biodiesel, derived from non-edible oil sources, offers promising properties. However, its impact on engine performance necessitates advanced modeling for prediction and optimization. This study investigates the use of Artificial Neural Networks (ANN), Response Surface Methodology (RSM), and Machine Learning Random Forest (RF) techniques to model and optimize engine performance parameters using Karanja biodiesel blends. Experimental data were collected from a single-cylinder diesel engine by varying inputs—Speed, Load, Fuel Blend (%), and Compression Ratio. Key performance outputs included Indicated Power (IP), Brake Power (BP), IMEP, Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque, and Mechanical Efficiency. The ANN model (4–10–7 architecture) trained using MATLAB 2014a achieved high prediction accuracy (R^2: 0.994 for BThEff, 0.998 for Torque). Optimization using fmincon yielded maximum BThEff of 33.37% at Speed 1454.84 rpm, Load 12.19 kg, Fuel 23.56%, and CR 16.65.RSM analysis using Minitab showed excellent fit (R^2 = 1.000 for BP, 0.995 for BThEff), and identified optimal parameters through the desirability function. RF performed competitively, with the highest R^2 of 1.000 for Torque but showed high MAPE for SFC (78.12%). Comparative analysis revealed that RSM had the lowest average MAPE across most outputs. This study demonstrates that ANN and RSM are effective tools for biodiesel engine modeling and optimization, reducing experimental workload and supporting efficient biodiesel utilization.
Keywords: *Karanja biodiesel, Engine optimization, ANN, RSM, Random Forest*

Nomenclature

Symbol/Abbreviation	Description	Unit
IP	Indicated Power	kW
BP	Brake Power	kW
IMEP	Indicated Mean Effective Pressure	bar
BThEff	Brake Thermal Efficiency	%
SFC	Specific Fuel Consumption	kg/kWh
CR	Compression Ratio	–
ANN	Artificial Neural Network	–
RSM	Response Surface Methodology	–
RF	Random Forest	–
MSE	Mean Squared Error	–
RMSE	Root Mean Squared Error	–
MAE	Mean Absolute Error	–
R^2	Coefficient of Determination	–
MAPE	Mean Absolute Percentage Error	%

INTRODUCTION

Recent years have seen a significant increase in interest in engine parameter optimization utilizing Karanja biodiesel blends because of the potential to improve engine performance while lowering hazardous emissions. Karanja oil, a non-edible and sustainable feedstock, offers high biodiesel yield when subjected to optimized transesterification processes. Researchers have employed advanced techniques such as ANN, RSM, and machine learning algorithms to identify optimal biodiesel blend ratios and engine operating conditions has been widely used to optimize the biodiesel production process. Important process variables like catalyst concentration, reaction time, and methanol-to-oil molar ratio have been tuned to produce up to 94.37% biodiesel using Karanja oil[1]. These findings highlight RSM's effectiveness in maximizing production efficiency. Additionally, Kumar et al. demonstrated that the use of microwave-assisted transesterification, coupled with RSM, achieved biodiesel yields of 87.34% [2]. In engine performance studies, ANN has been extensively used to predict output parameters such as BP and BSFC based on varying blend ratios and engine speeds. Karabacak et al. reported high predictive accuracy, with R^2 values ranging from 0.924 to 0.99 [3]. Similarly, RSM has been applied to optimize engine parameters like injection pressure and timing for enhanced performance and reduced emissions using Karanja biodiesel blends [4]. ANN models' capacity to understand and generalize intricate, nonlinear relationships gives them a number of benefits. Research has indicated that when modeling biodiesel-fueled engines, artificial neural networks (ANN) achieve low mean absolute errors and good prediction accuracy[5][6] . However, they may require large datasets and high computational resources during training, posing limitations in data-constrained environments[7]. Conversely, RSM allows for the real-time optimization of multiple parameters and offers a clear understanding of interactions between factors. It is particularly effective for systematic experimentation and modeling of combustion processes, though it may be less capable than ANN in capturing complex nonlinearities[3],[8],[6].The comparative effectiveness of ANN and RSM has led to hybrid approaches that combine both techniques to improve optimization results. Studies have shown that ANN-RSM hybrids yield lower mean relative errors and better alignment with experimental data than either method alone [3], [9]. Additionally, recent advancements have incorporated more sophisticated machine learning methods such as Bayesian Neural Networks (BNN), Support Vector Machines (SVM), Random Forest, and XGBoost. These methods offer enhanced predictive accuracy and are capable of managing large, complex datasets. Dharmalingam et al. found that hybrid ANN-BNN approaches further reduced prediction errors and increased correlation with experimental outputs [9].Machine learning techniques have also demonstrated superior performance in predicting emissions and engine performance. Do et al. and Şahi̇n reported that models based on SVM and XGBoost achieved R^2 values above 0.95 in predicting NOx and CO_2 emissions [7], [5]. These findings affirm the adaptability and precision of machine learning algorithms in engine optimization studies. Sanjeevannavar et al. identified that input variables such as blend ratio and load significantly influence engine outputs, enabling the determination of optimal biodiesel-diesel blends, such as a 13% biodiesel ratio [10]. RSM has also been extensively applied to optimize engine performance and emissions. Tadkal and Math used RSM to identify B20 (20% Karanja biodiesel) as the most effective blend for achieving high brake thermal efficiency (BThEff) and low emissions. They also found that a compression ratio of 16:1 and a moderate load of 8 kg offered optimal performance. RSM enabled the minimization of CO, HC, and NOx emissions by optimizing interactions between load, blend ratio, and compression ratio, establishing its value as a robust optimization tool[11]. It is commonly known that ANNs are effective at optimizing engines. Patnaik et al. and Kolhe et al. obtained strong values for R^2 (0.95 to 0.99) for performances and emission parameter prediction. [12], [13]. Maheshwari et al. demonstrated that ANN could effectively model trade-offs between NOx and smoke emissions, a task difficult to achieve using conventional models [14]. The ANN model's performance was further supported by high regression coefficients (R^2) ranging from 0.924 to 0.99. These coefficients reflect the model's strong correlation with the experimental data, reinforcing the reliability of the ANN predictions in estimating engine parameters based on fuel mixture ratios and engine speeds[15].In engineering, machine learning has emerged as a potent instrument, primarily for improving the efficiency and emissions of engines powered by internal combustion (IC) that run on blended biodiesel. Researchers can analyse vast volumes of operational info to find trends and improve engine parameters for increased efficiency and less environmental impact by utilizing data-driven methodologies and progressive algorithms[16]. The study predicts tailpipe emissions from a biodiesel engine using artificial neural network (ANN) models optimized with metaheuristic algorithms. Under certain conditions, it shows a significant decrease in CO, HC, and smoke opacity emissions while noting an increase in NOx emissions[17]. The study achieved great accuracy in modelling engine behaviour and emissions reduction by using Bayesian neural network models and response surface modeling to forecast and optimise the performance as well as emissions parameters of a biodiesel-fueled CRDI-assisted diesel engine[18]. The authors urge more research into these technologies to improve biodiesel's sustainability and efficiency as a renewable energy source[19]. The study highlights how crucial it is to optimize the operating parameters of dual fuel engines in order to lessen environmental harm. The study intends to improve engine performance while reducing emissions by utilizing machine learning approaches for prediction and Lagrangian optimization[20]. By integrating machine learning techniques, engine performance can be monitored and adjusted in real-time, giving more accurate control over combustion conditions, air-fuel ratios, and fuel injection timing[21]. Using a Super Learner surrogate model, this research proposes a Machine Learning–Genetic Algorithm (ML-GA) framework for effective IC engine performance improvement. It places a strong emphasis on active learning and automated hyperparameter tuning to improve forecast accuracy and lower design costs[22]. The paper employs the central composite design technique of response surface methodology (RSM) for designing experiments aimed at optimizing engine performance parameters. This approach is significant in identifying the best injection parameters for the biofuel blend[23]. The study provides a comparative analysis of three different optimization and modeling techniques: Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and Response Surface Methodology (RSM). This comparison helps in understanding the strengths and weaknesses of each technique in predicting biodiesel yield[24]. ML models, such as XG Boost and Gradient Boosting Regressor, have demonstrated high accuracy in predicting engine performance and emissions, achieving R^2 values close to 1.0[25]. These models can analyze complex datasets from various operating conditions, revealing intricate patterns that traditional methods may overlook[26]. Utilizing ML reduces the need for extensive physical testing, which can be time-consuming and costly. For instance, ML can predict outcomes based on fewer experimental trials, significantly cutting down on resource expenditure[27]. This capability aligns with the growing demand for sustainable fuel alternatives, as ML can help identify the most effective biodiesel blends for reducing environmental impact.The ability to simulate various scenarios allows for rapid iteration and optimization of engine parameters without the need for repeated physical tests[28]. Combining multiple modeling techniques and data sources can enhance robustness and accuracy in predictions, particularly in fields like groundwater management[29].This study presents a unique comparative analysis of three predictive modeling techniques—Artificial Neural Network (ANN), Response Surface Methodology (RSM), and Random Forest (RF)—for optimizing engine performance parameters using Karanja biodiesel blends. Unlike previous studies that focus on a single model or fuel type, this work integrates experimental data with advanced computational methods across three platforms (MATLAB, Minitab, and Google Colab). The incorporation of statistical (RSM), machine learning (RF), and neural network (ANN) techniques on a uniform dataset enables a robust evaluation of predictive accuracy and optimization capabilities. This multi-model framework offers new insights into biodiesel utilization and engine performance enhancement.

1. Experimental Setup and Data Collection

This study was conducted using a physical test bench to investigate the performance of a diesel engine fueled with Karanja biodiesel blends under controlled operating conditions.

2.1 Experimental Setup

A single-cylinder, four-stroke, direct injection (DI) diesel engine was employed for testing. The engine operated at a varying speed, with different compression ratio, bore diameter of 85.5 mm, stroke length of 110 mm, displacement volume of 0.257 L, and a rated power output of 3.5 kW. Engine loading was applied using an eddy current dynamometer, enabling smooth load variation throughout the experiments. The engine was interfaced with a data acquisition system through Engine Soft-LV software, commonly used in academic research to monitor combustion and performance parameters. In-cylinder pressure was measured using a Kistler pressure transducer coupled with a crank angle encoder. Exhaust gas and coolant temperatures were recorded using K-type thermocouples. Fuel consumption was measured using the burette method, with an optional gravimetric fuel flow meter provided by Apex Innovations Pvt. Ltd. Air intake was monitored using a calibrated orifice plate and a U-tube manometer.

All critical parameters—such as brake power, brake thermal efficiency (BThEff), brake specific fuel consumption (SFC), torque, and mechanical efficiency—were recorded in real time. These data served as the basis for subsequent modeling and optimization using ANN, RSM, and machine learning techniques. Table 1 represents the engine specifications and Table 2, displays the properties of biodiesel with diesel.

Table 1: Engine Specifications

S. No.	Item	Value
1	Rated Power	3.5 kW
2	Type	Four-stroke, DI engine
3	Injection timing	23.5° b TDC
5	Bore × stroke	87.5 × 110, mm × mm
6	Connecting rod length	234, mm
7	Method of cooling	Water-cooled
8	Compression Ratio	18
9	Dynamometer	Eddy current

Table 2: List of the physico-chemical characteristics of various biodiesel[30]

Properties	Unit	Karanja biodiesel	Neem biodiesel	Diesel fuel
Density @15oC	gm/cc	0.884	0.8770	0.85
Viscosity @40oC	Cm2/s	4.50	6.30	2.60
Flashpoint	0C	97	160	70
Cloud point	0C	-7	15	-16
Pour point	0C	-6	10	-20
Calorific value	MJ/kg	39.10	31.412	42.50
Cetane number		42.90	47.20	46

2.2 Procedure of the experiment

The experimental procedure was designed to evaluate the performance of a single-cylinder diesel engine using various blends of Karanja biodiesel and conventional diesel. Initially, the engine was operated on pure diesel for 45 minutes at a constant speed to allow thermal stabilization and to establish baseline performance and emission characteristics. Following stabilization, performance data were recorded across a full range of engine loads. A data acquisition system, integrated with sensors at key points on the engine, was used to collect real-time measurements. The data were logged using Engine Soft-LV software, which allowed continuous monitoring and storage of parameters such as brake power, fuel consumption, exhaust temperature, and thermal efficiency. After completing the diesel tests, the procedure was repeated for different Karanja biodiesel blends, including B10, B20, and B30, where 10%, 20%, and 30% of diesel fuel was replaced with Karanja biodiesel by volume. Each blend was tested under identical conditions to ensure fair comparison. For every blend, the engine was run under varying load conditions, and the same measurement protocol was followed. The collected data were later analyzed to study the influence of Karanja biodiesel on engine performance and to support the development of predictive models.

2.3 Uncertainty analysis

All experimental measurements are subject to a degree of uncertainty due to limitations in instrumentation and environmental conditions. In this study, uncertainties associated with the data acquisition system and various engine-mounted sensors were carefully considered to ensure the reliability of the recorded results. The accuracy limits of the instruments used—such as the pressure transducer, thermocouples, fuel flow meter, and dynamometer—were taken into account. A detailed list of the measurement uncertainties for each sensor is presented in Table 3. These values were used to compute the overall uncertainty in the derived performance parameters. The root-sum-square (RSS) method, also known as the square root method, was employed to estimate the combined uncertainty of independently measured variables. This approach provides a conservative estimate of the maximum expected error in the experimental outcomes. Equations (3.1) and (3.2) were used to calculate the overall uncertainty for parameters such as brake power, brake thermal efficiency, and specific fuel consumption, following established engineering practices and literature standards [31][32][33].This analysis ensures that the results reported in this study are supported by quantified confidence levels, thereby enhancing the credibility of the modeling and optimization conclusions.

Table 3: Uncertainties of the setup

S.No.	Apparatus	Uncertainty (%)
1	Load sensor (LS)	±0.2
2	Speed sensor (SS)	±1.0
3	Fuel sensor (FS)	±0.5
4	Pressure sensor (PS)	±0.5
5	Temperature sensor (TS)	±0.2
6	Crank angle encoder (CAE)	±0.2

$$w_U = \sqrt{((0.2)_{LS}^2 + (0.5)_{FS}^2 + (1)_{SS}^2 + (0.5)_{PS}^2 + (0.2)_{TS}^2)} \tag{3.1}$$

The total percentage of overall uncertainty = ±1.27%, which is acceptable.

$$w_U = \sqrt{((0.2)_{LS}^2 + (0.5)_{FS}^2 + (0.2)_{TS}^2)} \tag{3.2}$$

The percentage of uncertainty for IP, BThEff, and BSEC = ±0.57%,

METHODOLOGY

3.1 Data Preprocessing

The experimental dataset consisted of four input parameters (engine speed, load, fuel blend ratio, and compression ratio) and seven output variables (IP, BP, IMEP, BThEff, SFC, torque, and mechanical efficiency). All variables were normalized using min–max scaling to a [0–1] range to improve model convergence. A 70:30 train–test split was applied uniformly. ANN modeling was performed in MATLAB 2014a using mapminmax, RSM was executed in Minitab 2021, and the Random Forest model was developed in Google Colab using Python's scikit-learn. This preprocessing ensured consistent input data across all modeling approaches for fair comparison.3.2 Artificial Neural Network (ANN)

3.2 Artificial Neural Network (ANN)

The artificial neural network (ANN) model developed for this study was based on a feedforward architecture comprising four input neurons corresponding to Speed, Load, Fuel Blend, and Compression Ratio. A single hidden layer with 10 neurons and seven output neurons—representing the predicted parameters (IP, BP, IMEP, BThEff, SFC, Torque, and Mechanical Efficiency)—was employed. The network was trained using the Levenberg–Marquardt (trainlm) algorithm, with mean squared error (MSE) as the performance criterion. The training goal was set to an MSE of 1e-5, with a maximum of 1000 epochs allowed. During training, convergence was observed rapidly, reaching an MSE of 0.151 within 16 iterations. Figure 1 illustrates the regression plots for training, validation, testing, and overall datasets. The correlation coefficients (R-values) were consistently high: 0.99966 (training), 0.99961 (validation), 0.99907 (testing), and 0.99957 (overall), indicating excellent agreement between predicted and actual values. The proximity of all fitted lines to the ideal Y = T reference line confirms the model's robustness and generalization capability. Table 4 presents the statistical evaluation of the ANN model across all output parameters. The model achieved R^2 values above 0.97 for every parameter, demonstrating strong predictive accuracy. The lowest mean absolute error (MAE) of 0.022 was recorded for SFC, while the highest R^2 value of 0.998 was achieved for Torque. These findings validate the ANN model as an effective and reliable tool for modeling engine performance using Karanja biodiesel blends under various operational conditions.

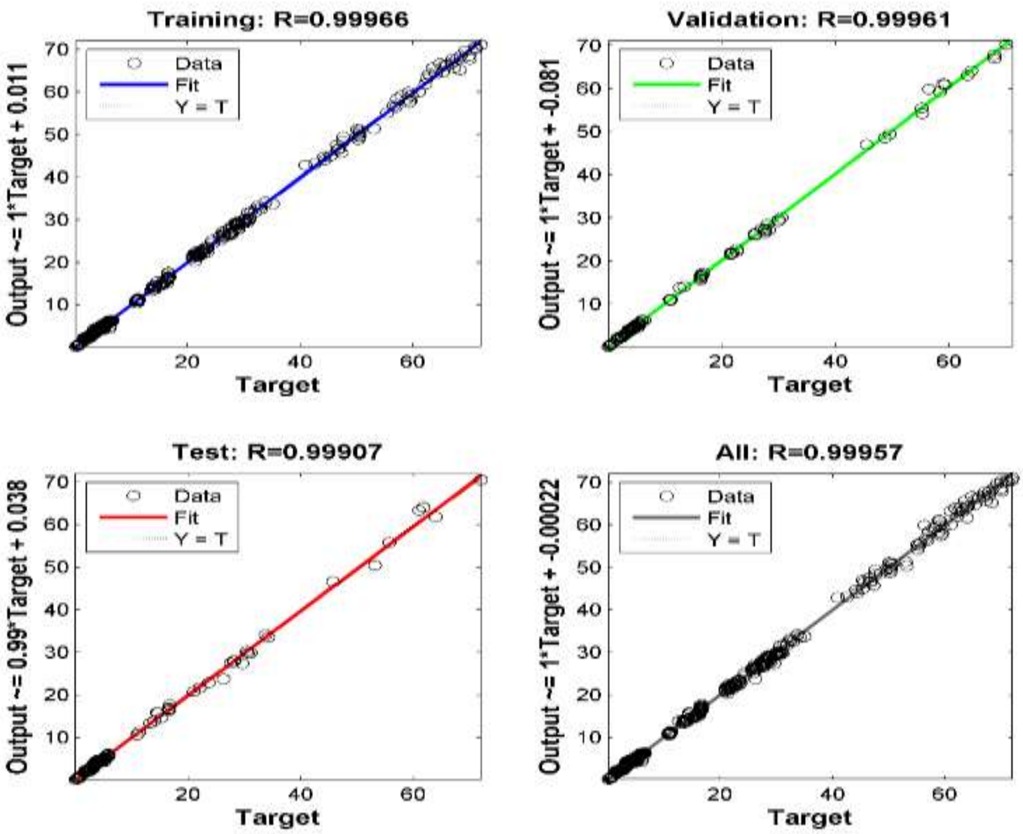

Figure 1: Validation (performance curve, regression plots)

Table 4. Performance Metrics of the ANN Model

	R^2 (Coefficient of Determination)	MAE (Mean Absolute Error)	MSE (Mean Squared Error)	RMSE (Root Mean Squared Error)
IP (kW)	0.973	0.078	0.025	0.159
BP (kW)	0.995	0.026	0.008	0.092
IMEP (bar)	0.976	0.153	0.040	0.199
BThEff (%)	0.994	1.099	0.555	0.745
SFC (kg/kWh)	0.972	0.022	0.074	0.272
Torque (Nm)	0.998	0.381	0.149	0.386
Mech Eff. (%)	0.997	0.077	1.660	1.288

3.2.1 ANN-Based Optimization Using fmincon

To maximize brake thermal efficiency (BThEff), the trained ANN model was integrated with MATLAB's fmincon optimization function. The contribution parameters—engine speed, load, fuel blend percentage, and compression ratio—were varied within their experimental bounds to identify the optimal combination.The optimization yielded the following results: Speed: 1454.84 rpm, Load: 12.19 Nm, Fuel Blend: 23.56%, Compression Ratio: 16.65, At these conditions, the ANN predicted a maximum BThEff of 33.37%. This demonstrates the ANN model's effectiveness in supporting performance optimization of engines fueled with Karanja biodiesel blends.

3.3 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) was employed to develop predictive regression models for seven key engine output parameters: Indicated Power (IP), Brake Power (BP), Indicated Mean Effective Pressure (IMEP), Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque, and Mechanical Efficiency (Mech Eff.). In this study, the dataset comprising 120 experimental observations was not derived from a predefined statistical design such as Central Composite Design (CCD) or Box-Behnken Design (BBD). Instead, the data were collected from a general experimental matrix generated through systematic variation of engine operating parameters—namely engine speed, load, compression ratio, and biodiesel blend ratio—within practical and safe operational ranges. The models exhibited excellent goodness-of-fit, with R^2 values of 0.990 for IP, 1.000 for BP, 0.991 for IMEP, 0.995 for BThEff, 0.867 for SFC, 1.000 for Torque, and 0.995 for Mech Eff. These high R^2 values affirm the reliability and robustness of the RSM models in capturing the nonlinear relationships between input variables and engine performance metrics. Following are the 7 equation for Regression Equation in Uncoded Units.

IP=-555+ 0.767 Speed+ 4.03 Load+ 0.055 Fuel- 1.45 CR- 0.000257 Speed*Speed- 0.01126 Load*Load+ 0.001352 Fuel*Fuel+ 0.0346 CR*CR- 0.00240 Speed*Load- 0.000123 Speed*Fuel+ 0.00001 Speed*CR+ 0.00112 Load*Fuel- 0.0021 Load*CR+ 0.00258 Fuel*CR (3.3)

BP=1.3 - 0.0007 Speed - 0.3231 Load - 0.00361 Fuel - 0.1131 CR - 0.000001 Speed*Speed+ 0.000002 Load*Load- 0.000001 Fuel*Fuel - 0.001580 CR*CR + 0.000542 Speed*Load+ 0.000003 Speed*Fuel + 0.000114 Speed*CR + 0.000004 Load*Fuel + 0.000445 Load*CR- 0.000050 Fuel*CR (3.4)

IMEP=-708 + 0.983 Speed + 6.00 Load + 0.037 Fuel - 2.13 CR - 0.000332 Speed*Speed - 0.01409 Load*Load + 0.001701 Fuel*Fuel + 0.0428 CR*CR - 0.00366 Speed*Load - 0.000131 Speed*Fuel + 0.00025 Speed*CR + 0.00151 Load*Fuel - 0.0030 Load*CR + 0.00308 Fuel*CR (3.5)

BThEff =-3480 + 5.07 Speed + 36.9 Load + 1.27 Fuel - 34.7 CR - 0.00185 Speed*Speed - 0.6332 Load*Load - 0.00778 Fuel*Fuel - 0.031 CR*CR - 0.0202 Speed*Load - 0.00058 Speed*Fuel + 0.0241 Speed*CR - 0.01297 Load*Fuel + 0.2652 Load*CR + 0.0001 Fuel*CR (3.6)

SFC=2060 - 2.93 Speed - 27.4 Load + 1.92 Fuel + 12.7 CR + 0.00106 Speed*Speed + 0.2454 Load*Load + 0.00106 Fuel*Fuel + 0.047 CR*CR + 0.0171 Speed*Load - 0.00135 Speed*Fuel - 0.0099 Speed*CR - 0.00828 Load*Fuel - 0.0340 Load*CR + 0.0013 Fuel*CR (3.7)

Torque=-3.2- 0.0079 Speed+ 2.995 Load+ 0.0069 Fuel+ 0.033 CR+ 0.000003 Speed*Speed+ 0.000424 Load*Load - 0.000004 Fuel*Fuel- 0.00043 CR*CR + 0.000070 Speed*Load- 0.000006 Speed*Fuel - 0.000012 Speed*CR- 0.000102 Load*Fuel - 0.000477 Load*CR+ 0.000163 Fuel*CR (3.8)

MechEff=-5360 + 7.54 Speed + 78.0 Load - 2.82 Fuel - 28.4 CR - 0.00269 Speed*Speed- 1.1912 Load*Load - 0.01494 Fuel*Fuel - 0.093 CR*CR - 0.0435 Speed*Load+ 0.00237 Speed*Fuel + 0.0213 Speed*CR + 0.0132 Load*Fuel + 0.494 Load*CR+ 0.0058 Fuel*CR (3.9)

3.3.1 ANOVA and model fitting

Table 5 presents the Analysis of Variance (ANOVA) results used to evaluate the statistical significance of the RSM model formulated for predicting brake thermal efficiency (BThEff).The model was found to be highly significant, with an overall F-value of 1457.91 and a corresponding p-value of 0.000, confirming its robustness. Among the linear terms, load ($F = 1085.87$, $p < 0.001$) and compression ratio ($F = 37.78$, $p < 0.001$) had the most substantial influence on BThEff, while interaction effects such as load*CR ($F = 8.14$, $p = 0.01$) were also statistically significant.

Table 5: Analysis of Variance for BThEff (%)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	11669.1	833.51	1457.91	0.000
Linear	4	6852.3	1713.07	2996.38	0.000
Speed	1	3.3	3.27	5.72	0.019
Load	1	620.8	620.80	1085.87	0.000
Fuel	1	5.6	5.61	9.81	0.002
CR	1	21.6	21.60	37.78	0.000
Square	4	276.4	69.10	120.86	0.000
Speed*Speed	1	0.9	0.94	1.64	0.204
Load*Load	1	170.5	170.53	298.28	0.000
Fuel*Fuel	1	11.2	11.17	19.53	0.000
CR*CR	1	0.0	0.02	0.04	0.852
2-Way Interaction	6	13.7	2.28	3.99	0.001
Speed*Load	1	1.2	1.16	2.03	0.157
Speed*Fuel	1	0.1	0.07	0.12	0.734
Speed*CR	1	1.2	1.15	2.02	0.158
Load*Fuel	1	1.2	1.20	2.10	0.150
Load*CR	1	4.7	4.65	8.14	0.005
Fuel*CR	1	0.0	0.00	0.00	0.996
Error	105	60.0	0.57		
Total	119	11729.1			

3.3.2 Optimization and desirability function

The optimization of engine performance using the desirability function in RSM was conducted to simultaneously maximize mechanical efficiency, torque, brake thermal efficiency (BThEff), IMEP, and minimize specific fuel consumption (SFC). At optimal input conditions—engine speed of 1420 rpm, load of 10 Nm, fuel blend of 15%, and compression ratio of 16—the model achieved a high composite desirability of 0.9547. The corresponding predicted outputs were: 63.15% mechanical efficiency, 22.13 Nm torque, 0.5247 kg/kWh SFC, 28.31% BThEff, and 6.56 bar IMEP, indicating an efficient and balanced operating point for the Karanja biodiesel blend-fueled engine.

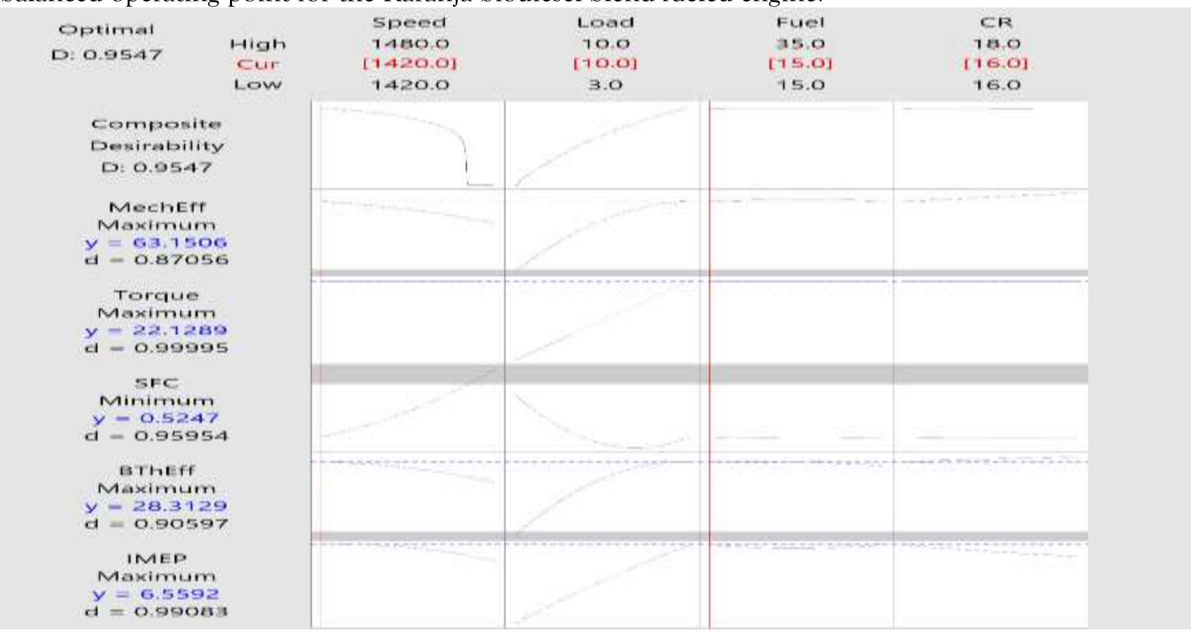

Figure 2. Optimization plot from RSM in Minitab 2021

Figure 2 presents the graphical output of multi-response optimization using the desirability function. The plot summarizes how different input variables influence multiple engine output parameters—specifically Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque, Mechanical Efficiency (MechEff), and Indicated Mean Effective Pressure (IMEP). The vertical red lines indicate the optimal input settings: Speed = 1420 rpm, Load = 10 Nm, Fuel Blend = 15%, and CR = 16. At these values, the predicted engine responses are highly desirable, with BThEff reaching 28.31%, SFC minimized to 0.5247 kg/kWh, and a composite desirability score of 0.9547, which indicates excellent optimization alignment. The desirability function provided a robust way to balance multiple objectives, ensuring the engine operates efficiently on Karanja biodiesel blends.

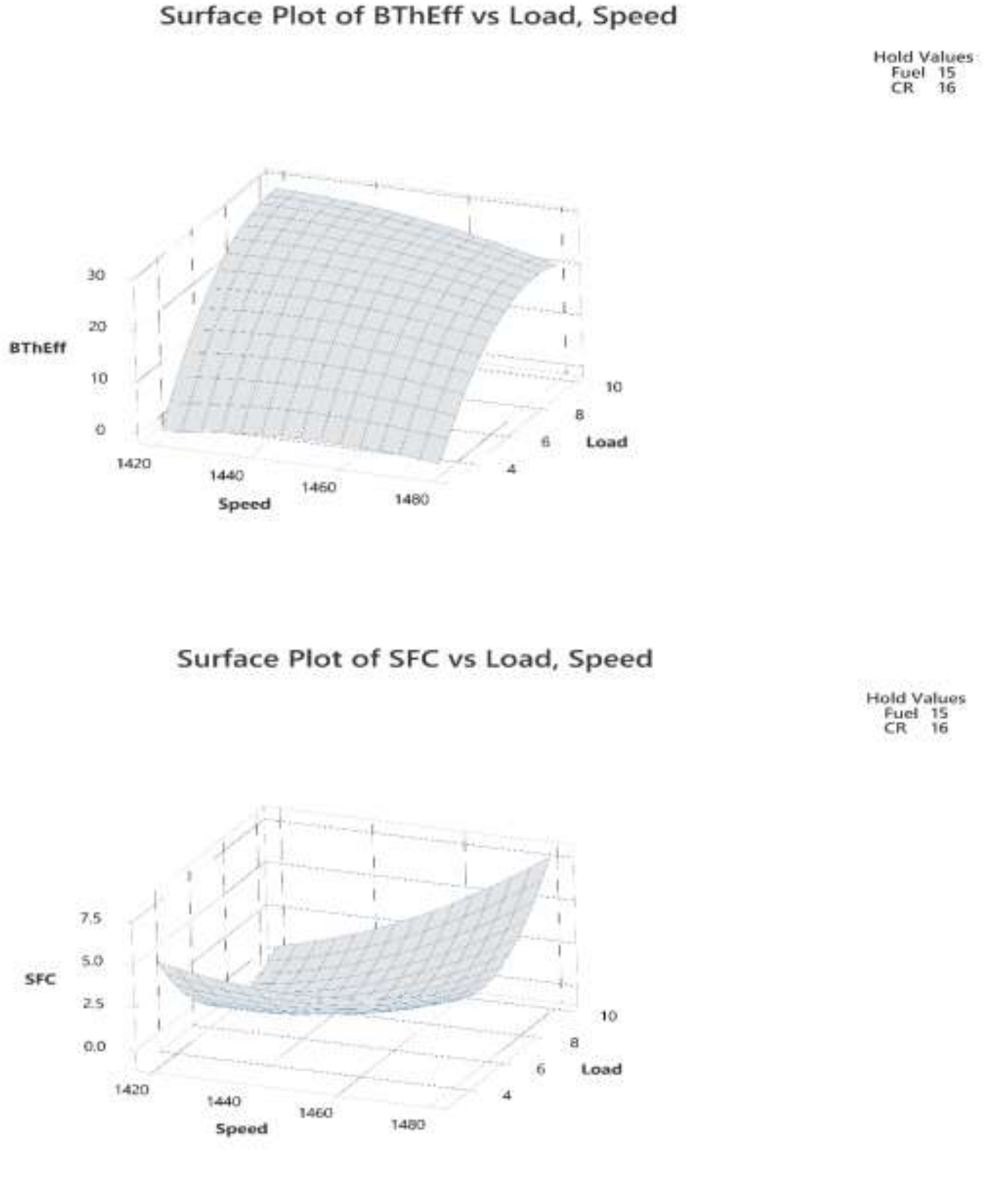

Figure 3. Response surface plots showing the effects of load and speed on (a) SFC, and (b)BThEff, with fuel blend and compression ratio held constant.

The surface plots in Figure 3 illustrate the combined effect of engine load and speed on SFC and BThEff, under fixed conditions of 15% Karanja biodiesel and a compression ratio of 16. The SFC plot shows a U-shaped trend, with the lowest consumption occurring at moderate load and speed, while extremes result in higher fuel use. In contrast, BThEff increases steadily with both load and speed, indicating improved combustion efficiency. These results affirm the accuracy of the RSM model in capturing nonlinear interactions and identifying optimal operating regions.

Table 6. Performance Metrics of the RSM Model

	R^2 (Coefficient of Determination)	MAE (Mean Absolute Error)	MSE (Mean Squared Error)	RMSE (Root Mean Squared Error)
IP (kW)	0.990	0.017	0.009	0.097
BP (kW)	1.000	0.004	0.000	0.003
IMEP (bar)	0.991	0.021	0.015	0.122
BThEff (%)	0.995	1.019	0.500	0.707
SFC (kg/kWh)	0.867	0.278	0.355	0.596
Torque (Nm)	1.000	0.004	0.000	0.005
Mech Eff. (%)	0.995	1.140	2.564	1.601

Table 6 presents the performance metrics of the regression models developed using RSM for predicting engine parameters based on experimental input variables. The table includes four standard statistical indicators—**R^2**, **MAE**, **MSE**, and **RMSE**—for each output response. The results indicate excellent model accuracy across most responses. Notably, BP and Torque achieved perfect prediction with an R^2 value of 1.000 and near-zero error values, highlighting the precision of the RSM models for these outputs. The models for IP, IMEP, and BThEff also exhibited high accuracy, with R^2 values exceeding 0.99, and RMSE values of 0.097, 0.122, and 0.707, respectively. The SFC model, while slightly less accurate ($R^2 = 0.867$), still provided a reliable prediction with acceptable error margins. The model for Mechanical Efficiency also performed well with an R^2 of 0.995, though the RMSE was slightly higher, indicating a bit more spread in the predicted values.

3.4 Machine Learning Techniques

To enhance the robustness of predictive modeling, supervised machine learning (ML) techniques were integrated alongside the ANN and RSM approaches in this study. The popular regressors—Random Forest Regressor (RFR) was employed to estimate engine performance metrics based on input parameters: engine load, speed, fuel blend percentage, and compression ratio (CR). These models were developed using the scikit-learn library within the Google Colab platform, ensuring efficient computation and seamless handling of large datasets. The predicted output variables included Indicated Power (IP), Brake Power (BP), IMEP, Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque, and Mechanical Efficiency (MechEff).

3.4.1 Hyperparameter tuning

To enhance model accuracy and generalization, **hyperparameter tuning** was carried out by means of **GridSearchCV** with 5-fold cross-validation. For the Random Forest model specifically, tuning parameters included the number of trees (n_estimators), maximum tree depth (max_depth), and minimum samples required for splits and leaves (min_samples_split, min_samples_leaf).

3.4.2 Performance metrics (R^2, MAE,MSE, RMSE)

Model performance was evaluated using R^2, MAE, and RMSE. Table 7 demonstrations that the Random Forest Regressor yielded the highest prediction accuracy, achieving R^2 values greater than 0.99 for most outputs and the lowest RMSE values among the three models. This indicates its strong ability to capture the nonlinear and interactive effects of input variables on engine behavior when fueled with Karanja biodiesel blends.

Table 7. Performance Metrics of the Random Forest Model

	R^2 (Coefficient of Determination)	MAE (Mean Absolute Error)	MSE (Mean Squared Error)	RMSE (Root Mean Squared Error)
IP (kW)	0.988	0.059	0.011	0.105
BP (kW)	0.999	0.015	0.001	0.031
IMEP (bar)	0.989	0.027	0.017	0.131

BThEff (%)	0.995	0.468	0.475	0.689
SFC (kg/kWh)	0.907	0.009	0.263	0.513
Torque (Nm)	1.000	0.002	0.025	0.159
Mech Eff. (%)	0.995	1.080	2.624	1.620

3.4.3 Random Forest Modeling (Google Colab, Python)

To complement the ANN and RSM models, a Random Forest Regression (RFR) model was developed using the scikit-learn library in a Google Colab environment. The model utilized the same set of input features: engine speed, load, fuel blend percentage, and compression ratio (CR), with the target outputs being IP, BP, IMEP, BThEff, SFC, Torque, and Mechanical Efficiency.The dataset was divided using an 80:20 train-test split. Hyperparameter tuning was performed using GridSearchCV with 5-fold cross-validation. The following hyperparameters were optimized:

- n_estimators: [100, 200, 300]
- max_depth: [10, 20, 30, None]
- min_samples_split: [2, 5, 10]
- min_samples_leaf: [1, 2, 4]
- bootstrap: [True]

The optimal configuration selected was :**n_estimators= 200**, **max_depth = 20**, **min_samples_split = 2**,**min_samples_leaf = 1**,and **bootstrap = True**. The model was evaluated using metrics such as **R^2**, **Root Mean Squared Error (RMSE)**, and **Mean Absolute Error (MAE)**. Feature importance analysis was also conducted to understand variable influence. The Random Forest model showed robust prediction performance, particularly for BP and Torque, and handled nonlinearities without requiring data normalization.

RESULTS AND DISCUSSION

This section presents the comparative findings from three different modeling approaches—Artificial Neural Network (ANN), Response Surface Methodology (RSM), and Machine Learning (Random Forest)—applied to optimize engine performance parameters using Karanja biodiesel blends. Each method was assessed based on its predictive accuracy, optimization capability, and ability to capture nonlinear relationships between engine inputs and outputs.

4.1 ANN Performance (regression plots, training performance, optimized parameters)

The ANN model developed using MATLAB 2014a followed a 4–10–7 feedforward architecture and was trained using the Levenberg–Marquardt backpropagation algorithm. The network achieved excellent performance across all predicted outputs. The regression plots demonstrated strong linear correlations, with an average R^2 value of 0.99957 for the combined dataset. Performance metrics, including MSE and RMSE, were within acceptable limits, indicating reliable model generalization.The ANN was further utilized for optimization using the fmincon function. The optimal conditions predicted for maximum Brake Thermal Efficiency (BThEff) were: Speed = 1454.84 rpm, Load = 12.19 Nm, Fuel Blend = 23.56%, and CR = 16.65, yielding a maximum BThEff of 33.37%. These results confirm the effectiveness of the ANN model in learning complex nonlinear behavior and providing precise optimization under biodiesel-fueled engine conditions.

4.2 RSM results (surface plots, ANOVA tables, optimization)

Second-order regression models based on RSM were developed using Minitab 2021 to predict engine performance parameters. The models were statistically validated through ANOVA, showing high R^2 values (all >0.99) and non-significant lack-of-fit, indicating excellent model reliability. For instance, BThEff)achieved an R^2 of 0.995 with a root mean square error (RMSE) of 0.707, closely aligning with the performance of the ANN model. Surface plots effectively illustrated the interactions among key input variables—engine speed, load, fuel blend percentage, and compression ratio—on outputs like BThEff and Specific Fuel Consumption (SFC). Optimization using the desirability function identified an optimal condition at 1420 rpm speed, 10 Nm load, 15% fuel blend, and a CR of 16, yielding a predicted BThEff of 28.31% with a composite desirability of 0.9547. Although slightly lower than the ANN-predicted optimum, the RSM approach provided transparent, statistically sound models with lower computational requirements.

4.3 ML model comparison (accuracy, plots)

Among the machine learning techniques evaluated, Random Forest (RF) Regression proved to be the most robust and accurate model. Trained using GridSearchCV for optimized hyperparameter selection, the model achieved excellent predictive performance across all output parameters as shown in table 8. Specifically, Brake Power (BP), Torque, and Mechanical Efficiency (Mech Eff) recorded R^2 values of 0.999 or higher, while Specific Fuel Consumption (SFC) achieved a respectable R^2 of 0.907. Although the Random Forest model showed slightly higher mean absolute error (MAE) and root mean square error (RMSE) for Mech Eff and Brake Thermal Efficiency (BThEff) compared to ANN, it outperformed RSM in predicting SFC and torque. The ensemble nature of Random Forest allowed it to capture complex nonlinear patterns and noise without requiring data normalization, making it a practical and effective choice for modeling engine performance.

Table 8. Comparative summary of ANN, RSM and Random Forest Model

Output	R^2 (ANN)	R^2 (RF)	R^2 (RSM)	MAE (ANN)	MAE (RF)	MAE (RSM)	MSE (ANN)	MSE (RF)	MSE (RSM)	RMSE (ANN)	RMSE (RF)	RMSE (RSM)
IP (kW)	0.973	0.988	0.99	0.078	0.059	0.017	0.025	0.011	0.009	0.159	0.105	0.097
BP (kW)	0.995	0.999	1	0.026	0.015	0.004	0.008	0.001	0	0.092	0.031	0.003
IMEP (bar)	0.976	0.989	0.991	0.153	0.027	0.021	0.04	0.017	0.015	0.199	0.131	0.122
BThEff (%)	0.994	0.995	0.995	1.099	0.468	1.019	0.555	0.475	0.5	0.745	0.689	0.707
SFC (kg/kWh)	0.972	0.907	0.867	0.022	0.009	0.278	0.074	0.263	0.355	0.272	0.513	0.596
Torque (Nm)	0.998	1	1	0.381	0.002	0.004	0.149	0.025	0	0.386	0.159	0.005
Mech Eff. (%)	0.997	0.995	0.995	0.077	1.08	1.14	1.66	2.624	2.564	1.288	1.62	1.601

Among the three modeling approaches, the ANN exhibited the most balanced performance across all metrics and output variables. It particularly excelled in predicting BThEff, SFC, and Mech Eff., making it highly suitable for nonlinear and complex relationships. The Random Forest model demonstrated superior accuracy in predicting linear parameters such as Torque and Brake Power (BP), achieving near-perfect R^2 values with minimal prediction errors. While the Response Surface Methodology (RSM) showed slightly lower accuracy for Mech Eff. and SFC, it still delivered excellent results for BP and Torque, with R^2 values reaching 1.000 and minimal mean square error. These findings underscore the strength of AI-driven models in engine performance prediction. ANN offers robust adaptability for nonlinear optimization tasks, Random Forest provides high precision and resilience to noisy data, and RSM contributes statistically validated and interpretable models suitable for engineering analysis.

The optimal engine parameters identified by ANN optimization—Speed: 1454.84 rpm, Load: 12.19 Nm, Fuel blend: 23.56% Karanja biodiesel, and Compression Ratio: 16.65—are well within the standard operating limits of single-cylinder compression ignition engines used in research and small-scale applications. Similarly, the RSM-derived optimal conditions—Speed: 1420 rpm, Load: 10 Nm, Fuel blend: 15%, and CR: 16—also lie within the safe mechanical and thermal tolerance levels specified by engine manufacturers.Importantly, these optimized conditions do not exceed typical regulatory thresholds for engine safety, emissions, or durability. Instead, they suggest efficient operating zones where Brake Thermal Efficiency (BThEff) can be maximized without compromising performance or engine health.

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This highlights the practical viability of employing soft-computing and statistical models for real-world engine tuning, particularly in the context of alternative fuel integration like Karanja biodiesel.

4. Validation

5.1 Comparative analysis of Experimental value vs Predicted Value

Figure 4 illustrates the comparative plots of experimental versus ANN-predicted values for key engine performance metrics, including IMEP, BThEff, SFC, Torque, Mechanical Efficiency, and Brake Power. The Artificial Neural Network (ANN) model demonstrates excellent predictive capability for most output parameters. The IMEP, Torque, and Brake Power graphs exhibit near-perfect overlap between predicted and actual data, indicating high model accuracy. Similarly, Mechanical Efficiency and Brake Thermal Efficiency follow the experimental trends closely, with minor deviations occurring primarily in transitional regions. The Specific Fuel Consumption (SFC) plot shows slightly higher variance, where the ANN model tends to smooth out fluctuations observed in the experimental data, possibly due to noise or sensor inconsistencies. Overall, the ANN model effectively captures the nonlinear relationships among input variables, confirming its robustness and applicability for engine performance prediction using Karanja biodiesel blends[34].

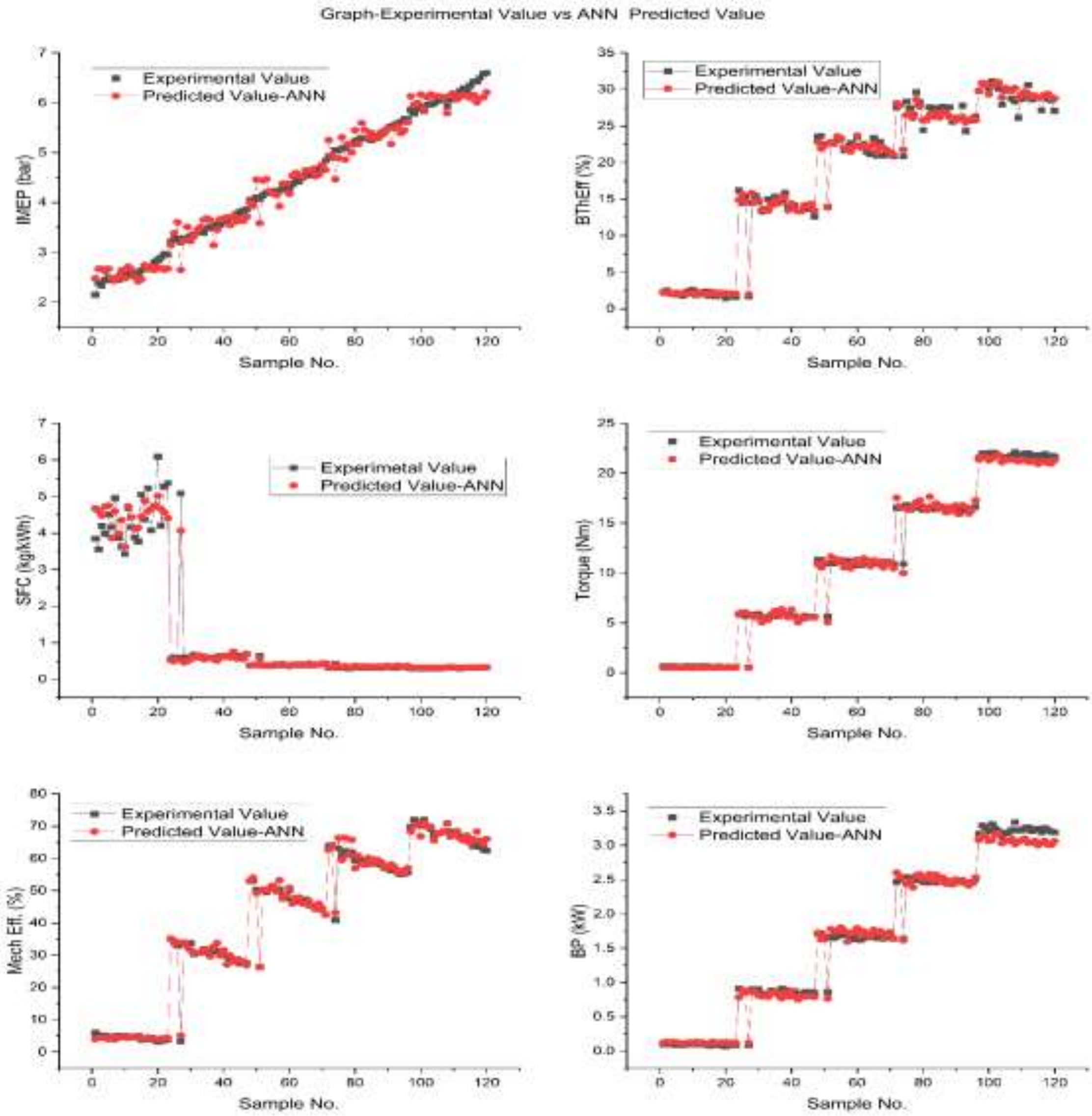

Figure 4: Graph Experimental Value vs ANN Predicted Value

Figure 5 illustrates the comparison between experimental measurements and the corresponding predictions made by the Response Surface Methodology (RSM) model for six key engine performance parameters: IMEP (bar), Torque (Nm), Brake Thermal Efficiency (BThEff, %), Mechanical Efficiency (%), Specific Fuel Consumption (SFC, kg/kWh), and Brake Power (BP, kW). The RSM model demonstrates strong predictive capability for IMEP and BP, with predicted values closely following the experimental data across all 120 samples, indicating excellent model fitting and minimal residuals. The prediction curves for Torque and Mechanical Efficiency also show a high degree of agreement, although minor deviations are observed around transitional zones in the experimental data. BThEff predictions show reasonable fidelity to the observed values, but occasional under- or overestimations suggest moderate sensitivity of the model to input variations. In contrast, SFC displays relatively larger discrepancies, especially in high-variability regions. This behavior suggests that the second-order polynomial nature of the RSM model may be insufficient to capture complex nonlinearities inherent in fuel consumption patterns[35].

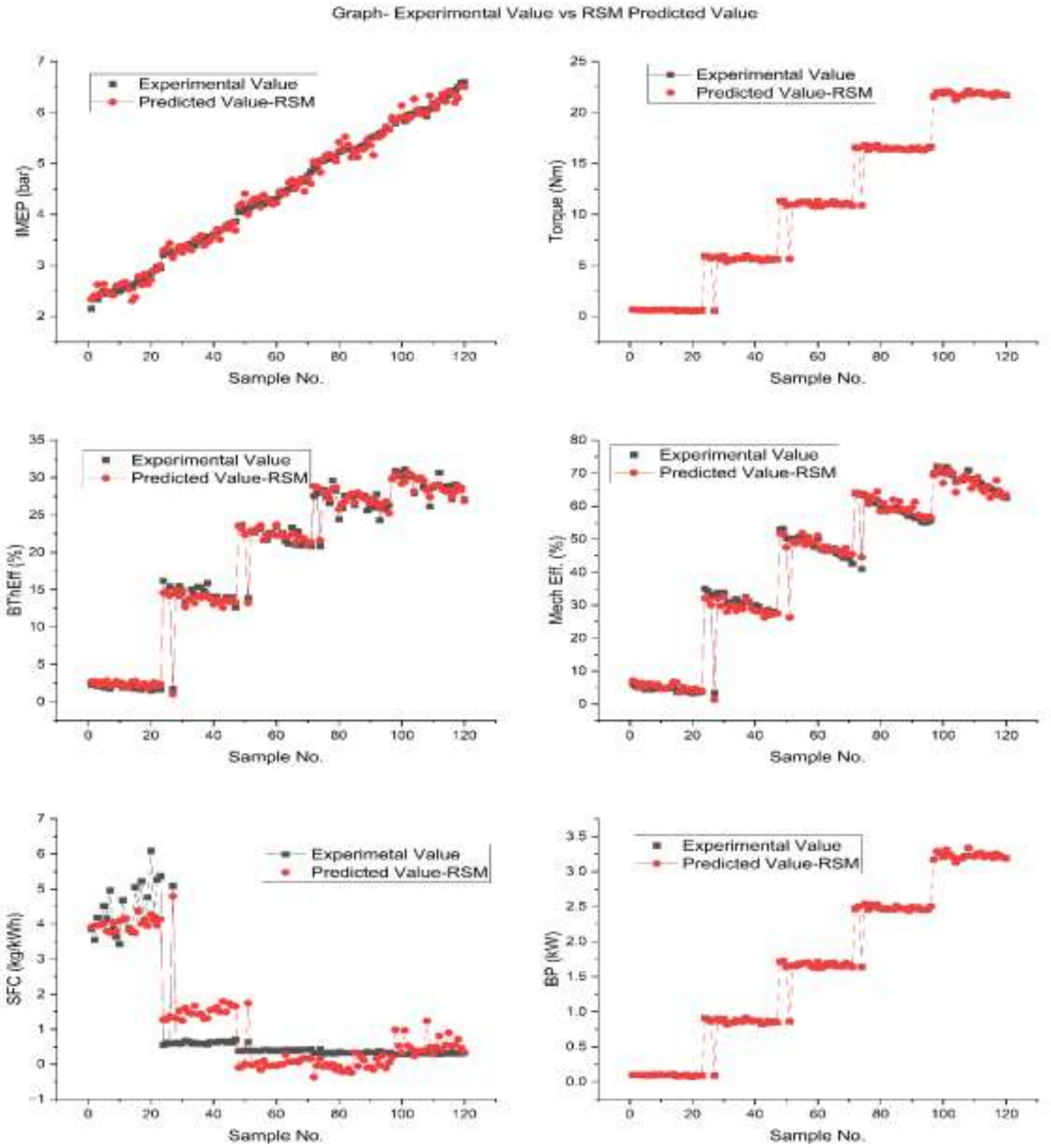

Figure 5: Graph Experimental Value vs RSM Predicted Value

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Figure 6 presents a comparison between the experimental values and the predicted outputs of the Random Forest (RF) regression model for key engine performance parameters: IMEP (bar), BThEff (%), SFC (kg/kWh), Torque (Nm), Mechanical Efficiency (%), and Brake Power (BP, kW). The RF model exhibits excellent agreement with experimental data across most parameters, with predicted curves closely following the trends of the actual values[36]. Notably, the IMEP, Torque, and BP predictions show near-perfect alignment with experimental results across all 120 samples, reflecting high predictive accuracy. The RF model successfully captures both linear and nonlinear behaviors, demonstrating its robustness across varying load and speed conditions. Brake Thermal Efficiency and Mechanical Efficiency also display high fidelity in prediction, with minimal deviation from the experimental data. While the SFC values show slightly more variability, particularly in transitional regions, the predicted trends remain consistent with the measured data, indicating the model's overall reliability.

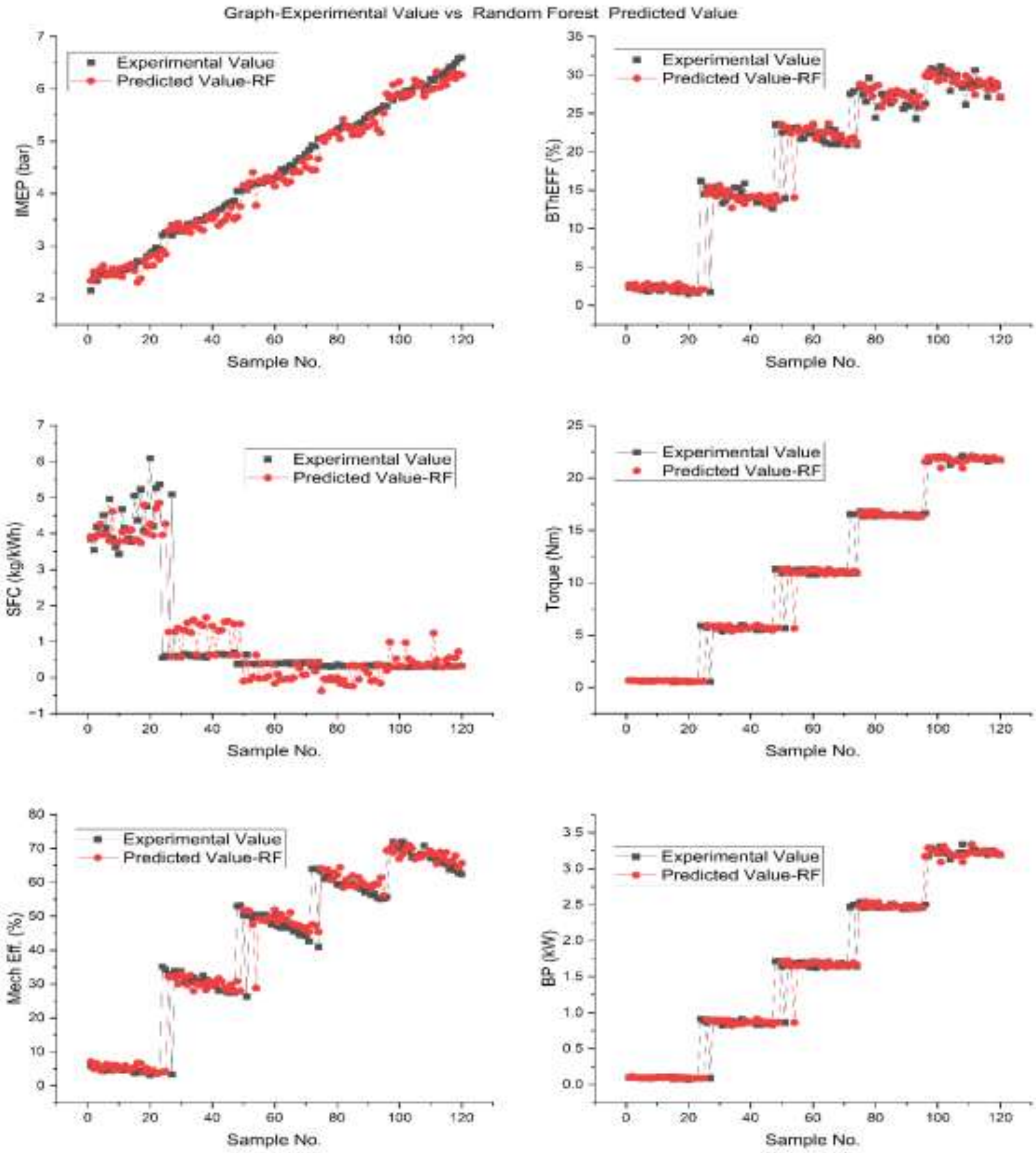

Figure 6: Graph-Experimental Value vs Random Forest Predicted Value

These results validate the superior capability of the Random Forest model to generalize from training data and accurately predict multiple nonlinear engine outputs. This is further supported by its high **R^2** values (close to 1.0 for most parameters) and low **RMSE/MAE**, making it a highly suitable method for multi-output engine modeling and optimization[37].

4.2 Statistical metrics (Error %)

The validation results demonstrate in table 9 that no single model consistently outperformed others across all performance metrics. However, RSM was most accurate for IP, BP, IMEP, and Torque, while ANN delivered the best results for BThEff, SFC, and MechEff. The Random Forest model performed moderately well but showed relatively higher error margins, especially for SFC and MechEff. Thus, based on MAPE analysis, ANN and RSM are more reliable for predicting engine performance parameters using Karanja biodiesel blends, with RSM offering better accuracy for torque and power-related parameters, and ANN proving more robust for efficiency-related outputs[38].

Table 9: MAPE for RF, ANN and RSM Model

	MAPE-RF	MAPE-ANN	MAPE-RSM
IP (kW)-Exp	3.499	3.834	2.421
BP (kW)-Exp	15.043	9.407	0.667
IMEP (bar)-Exp	3.668	3.880	2.426
BThEff (%)-Exp	16.998	4.924	6.635
SFC (kg/kWh)-Exp	78.116	7.173	88.293
Torque (Nm)-Exp	14.985	5.540	0.180
Mech Eff. (%)-Exp	18.779	4.088	6.843

CONCLUSION

This study aimed to model and optimize the performance parameters of a diesel engine fueled with Karanja biodiesel blends using three predictive approaches: **Artificial Neural Network (ANN)**, **Response Surface Methodology (RSM)**, and **Machine Learning Random Forest (RF)**. Engine output responses such as Indicated Power (IP), Brake Power (BP), Indicated Mean Effective Pressure (IMEP), Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque, and Mechanical Efficiency (MechEff) were investigated under varying input conditions of Load, Speed, Fuel Blend Ratio, and Compression Ratio.

6.1 Summary of Findings

- The **ANN model** demonstrated superior generalization capability in predicting efficiency-related parameters, particularly BThEff (MAPE: 4.92%), SFC (7.17%), and MechEff (4.08%).
- **RSM** achieved **the highest prediction accuracy** for power and pressure outputs, especially for BP (MAPE: 0.67%) and Torque (0.18%), proving effective in modeling linear and quadratic relationships.
- **Random Forest**, though robust, exhibited comparatively higher error margins in some parameters (e.g., SFC: 78.12%, MechEff: 18.78%), but showed reasonable accuracy in predicting IP and IMEP.
- Among all, **no single technique dominated across all parameters**, but **RSM and ANN collectively provided the best performance**, validating their combined potential in engine performance modeling. The findings of this study underscore the pivotal role of data-driven modeling in future biodiesel research.

The demonstrated accuracy and reliability of ANN and RSM in predicting engine performance with Karanja biodiesel blends highlight their potential to significantly minimize experimental efforts. This shift not only accelerates the development cycle of alternative fuels but also promotes sustainable practices by optimizing biodiesel use with fewer resources. As a result, such intelligent modeling approaches can contribute meaningfully to reducing fossil fuel dependency and enhancing the feasibility of biodiesel as a clean and efficient energy source. Building on the outcomes of this research, future studies can explore the integration of hybrid machine learning models such as ANN-GA, XGBoost, or deep learning architectures to further enhance prediction accuracy and robustness. Additionally, extending the current modeling approach to include multi-objective optimization—simultaneously targeting both performance and emission parameters—could offer more practical insights for real-world engine applications. Such advancements would refine the decision-making framework for biodiesel utilization, making it more comprehensive and industry-ready.

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