

Optimization of Engine Performance Parameters using PSO and GA for a Diesel Engine Operated with Karanja Biodiesel.

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Abstract:

This study investigates the enhancement of the braking thermal efficiency (BThEff) in a diesel engine running on Karanja biodiesel by optimizing four key engine performance parameters: engine speed, load, fuel blend ratio, and compression ratio. To approximate the link between input parameters and BThEff based on experimental data, a Random Forest (RF) model was used as a stand-in. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), two metaheuristic optimization methods, were used and contrasted throughout several separate experiments. The best parameter combinations were found via PSO and GA, both of which produced maximum BThEff values above 30%. GA converged more quickly (133.68 seconds) and had a marginally higher average BThEff (30.0665%) than PSO (30.0476%, 210.67 seconds). There was no discernible difference between the two approaches, according to statistical analysis employing t-tests and bootstrap validation ($p > 0.05$). The results show that both algorithms work well for increasing engine efficiency with biodiesel blends, however GA shows a little advantage in terms of consistency and computational economy. By optimizing engine tune, our effort enables the use of Karanja biodiesel as a sustainable fuel substitute.

Keywords: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Surrogate Modeling, Brake Thermal Efficiency (BThEff), Diesel Engine Optimization, Karanja Biodiesel

Nomenclature

Symbol Term	Description	Unit
BThEff	Brake Thermal Efficiency	%
SFC	Specific Fuel Consumption	kg/kWh
IP	Indicated Power	kW

BP	Brake Power	kW
IMEP	Indicated Mean Effective Pressure	bar
CR	Compression Ratio	-
PSO	Particle Swarm Optimization	-
GA	Genetic Algorithm	-
RF	Random Forest (Surrogate Model)	-
rpm	Revolutions per minute (Engine Speed)	rpm
Load	Engine Load	%
Fuel Blend	Volume percentage of Karanja biodiesel in the blend	%
T-test	Statistical test for comparing means	-
CI	Confidence Interval	%
n	Number of bootstrap resamples or trials	-

1. Introduction

The escalating global energy demand, coupled with the finite nature of fossil fuel reserves and the pressing environmental concerns arising from their combustion, has intensified research into sustainable and cleaner energy alternatives [1]. Internal combustion (IC) engines, particularly diesel engines, are significant contributors to atmospheric pollution, emitting greenhouse gases (GHG) and harmful pollutants such as nitrogen oxides (NO_x), particulate matter (PM), carbon monoxide (CO), and unburnt hydrocarbons (HC) [2]. This environmental impact necessitates a shift towards more sustainable fuel options and optimized engine operations [3].

Biodiesel has emerged as a promising renewable and biodegradable alternative fuel for compression ignition (CI) engines [4]. Derived from various feedstocks, including non-edible oils like Karanja, Pongamia, and waste cooking oil, biodiesel offers advantages such as lower toxicity, reduced sulfur content, and improved lubricity compared to conventional diesel [4], [5]. Studies have explored diverse biodiesel sources, including microalgae [6], [7], [8], waste cooking oil [9][10], and other non-edible seeds like Manilkara zapota [11] and Saraca asoca [12]. The production of biodiesel often involves transesterification, with research focusing on optimizing yield through various methods, including Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) [13]. For instance, optimizing Karanja oil biodiesel production has shown promising results in terms of yield and fuel properties [14], [15]. While biodiesel generally leads to reduced PM, CO, and HC

emissions due to its oxygen content, it can sometimes result in a slight increase in NO_x emissions and varying brake-specific fuel consumption (BSFC) [15], [16]. The integration of nano-additives like ZrO₂ or SiO₂ has also been investigated to further enhance performance and reduce emissions[8], [17], [18].

Optimizing engine operating parameters, such as engine speed, load, fuel blend ratio, compression ratio (CR), injection pressure (IP), and injection timing (IT), is crucial for maximizing engine efficiency and minimizing emissions when using biodiesel blends[11], [19]. The complex, non-linear relationships between these input parameters and engine responses make traditional experimental methods time-consuming and resource-intensive. Consequently, advanced statistical and computational methods, particularly artificial intelligence (AI) and meta-heuristic optimization algorithms, have gained prominence in engine research[5], [20], [21]. Techniques like Response Surface Methodology (RSM), Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) have been successfully applied to model, predict, and optimize biodiesel engine performance[4] [9] [22]. Hybrid approaches, combining metaheuristic algorithms with surrogate models or experimental designs, have further improved prediction accuracy and computational efficiency[19], [21]. A thorough comparison of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for diesel engine parameter optimization using Karanja biodiesel is still lacking, despite significant progress. This is particularly relevant for comparisons with surrogate models based on machine learning that have been statistically investigated. It is more challenging to develop more dependable engine tuning methods for wider biodiesel use because of this discrepancy. In order to bridge this gap, a thorough comparison of PSO and GA's performance, convergence behavior, and computational efficiency for diesel engine parameter optimization using Karanja biodiesel is being carried out in this study. In light of this, it is predicted that Genetic Algorithm (GA) will attain similar or marginally higher consistency in optimization results while exhibiting faster convergence and a notable decrease in computing time when compared to Particle Swarm Optimization (PSO). Our research uses both PSO and GA for engine parameter optimization, and builds a Random Forest-based surrogate model to address this. Our main contributions are a comparison of these methods that has been

statistically validated and the proof that GA reduces calculation time by 36.5% with greater consistency, offering useful information for engine tuning using Karanja biodiesel.

2. Materials and Methods

2.1 Data Description

The experimental data used in this study came from a single-cylinder diesel engine running on blends of Karanja biodiesel. With 120 observations spanning 11 variables, the dataset—saved as Karanja data.csv—captures both engine performance indicators and input parameters. The primary input features considered for optimization were: Engine speed (rpm), Load (%), Fuel blend ratio (%), Compression ratio (CR). The output variables included: Indicated Power (IP), Brake Power (BP), Indicated Mean Effective Pressure (IMEP), Brake Thermal Efficiency (BThEff), Specific Fuel Consumption (SFC), Torque (Nm), Mechanical Efficiency. The pandas package in Python was used to examine the dataset. A *df.info()* check verified that there were no missing values; every entry was complete and numeric. An engine speed range of 1400 to 1800 rpm, a load range of 0 to 90%, and a mean BThEff of roughly 18.94% were all disclosed by summary statistics *df.describe()*. The majority of test runs were carried out at moderate to high loads, and the average engine speed was approximately 1444 rpm. The training and optimization of the model were based on this tidy and organized dataset. For accurate forecast and parameter tweaking, it offered a representative range of actual engine operating circumstances.

2.2 Feature Selection

To determine which factors had the most impact on BThEff, a Random Forest model was used to do a feature importance analysis. The findings indicated that load was the most significant factor, accounting for more than half of the variation in BThEff. Other significant factors were engine speed, compression ratio, and fuel blend ratio. For the process of optimization, these four characteristics were chosen. A Random Forest Regressor with 100 estimators was used to do a feature importance analysis in order to comprehend the impact of the input parameters ('Speed', 'Load', 'Fuel', 'CR') on the goal variable ('BThEff'). Each input variable's relative contribution to forecasting the brake thermal efficiency is

shown by the feature importance that result, which are displayed in the "Feature Importance" plot and saved as *feature_importance.tiff*. This analysis confirmed the relevance of the selected attributes to the optimization objective.

2.3 Surrogate Modeling

To forecast BThEff, a 100-tree Random Forest Regressor was trained using the chosen characteristics. This model acted as a stand-in for intricate simulations or in-person testing. It enabled rapid and accurate evaluations during the optimization process. The Python *fit()* function was used to train the model. It could forecast BThEff values for any combination of input parameters after training. Both the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) procedures employed this prediction as the goal function. To approximate the intricate link between the input parameters (Speed, Load, Fuel, and CR) and the goal variable (BThEff), a Random Forest Regressor was used as a surrogate model. The available experimental data was used to train this surrogate model. The optimization algorithms (PSO and GA) can rapidly assess the predicted Brake Thermal Efficiency for different combinations of input parameters using this trained Random Forest model, which acts as a computationally effective stand-in for the real engine, eliminating the need for intricate simulations or physical experiments. Next, the PSO and GA algorithms' objective functions use the predictions from this surrogate model (*model.predict(X)*) to direct their search for the best parameters.

```
# =====  
# 📌 MODEL TRAINING  
# =====  
  
# Use Random Forest as surrogate model  
model = RandomForestRegressor(n_estimators=100)  
model.fit(df[features], df[target])
```

2.4 Particle Swarm Optimization (PSO)

PSO was utilized to determine the optimal engine parameter combination in order to optimize BThEff. To implement the algorithm, the *pyswarm* package was used. It was

decided to define the objective function as the negative of the predicted BThEff as it automatically addresses minimization concerns. The search space had the following boundaries: 0–90% load; 1400–1800 rpm speed, Fuel mixture: 15–20%, CR: 16–17, 50 particles were used during 30 iterations in each trial. To make sure it was consistent, the optimization was done ten times. The BThEff values and optimal solutions from every run were recorded and contrasted.

The objective function is the basis of the PSO implementation. Given that the purpose of the pso function is minimization, the objective function is defined as obtaining the expected BThEff's negative:

```
def objective(x):
    speed, load, fuel, cr = x
    X = pd.DataFrame([[speed, load, fuel, cr]], columns=features)
    y_pred = model.predict(X)
    return -y_pred[0]
```

In this function, x stands for a possible solution, which is a set of engine parameters: speed, load, fuel, and CR. These parameters are entered into the trained Random Forest surrogate model (model) in order to predict the corresponding BThEff. Since the negative value of this prediction (-y_pred[0]) is returned, maximizing the BThEff is the same as decreasing this value. According to table 1, the PSO algorithm's search space is constrained by upper and lower bounds for each parameter.

Table 1: Bounds for Engine Optimization Parameters

Parameter	Lower Bound (lb)	Upper Bound (ub)
Engine Speed (rpm)	1400	1800
Load (%)	0	90
Fuel Blend Ratio (%)	15	20
Compression Ratio (CR)	16	17

These bounds are set to guide the optimization within a relevant and feasible range of engine operation. To account for the algorithm's stochastic character and evaluate the consistency of the findings, the pso function was run for ten separate trials *range (10)*. Each trial had a maximum of 30 iterations *maxiter=30* and a swarm size of 50 particles

(*swarmsize=50*). For every trial, the corresponding optimal parameters (*xopt*) and the best achievable BThEff (which was transformed back to a positive value by negating the minimized objective function result, *-fopt*) were saved in the *pso_best* and *pso_results* lists). *tqdm* was used to track and display the trials' progress.

2.5 Genetic Algorithm (GA)

The DEAP package was used to create a Genetic Algorithm (GA) that maximizes brake thermal efficiency (BThEff) in order to optimize engine performance. Speed, load, fuel blend ratio, and compression ratio are the four engine parameters that each person in the population represented. The fitness evaluator used was the surrogate model, which was created with a Random Forest regressor. GA employed tournament selection (size = 3), blend crossover (), and Gaussian mutation () to direct the search. During crossover and mutation, bound restrictions were used to make sure that every individual stayed within practical operating bounds.

Table 2: Genetic Algorithm Configuration

Element	Description
Library	DEAP (Python)
Objective	Maximize BThEff
Evaluation	Surrogate model prediction (Random Forest)
Parameters Optimized	Speed, Load, Fuel Blend Ratio, Compression Ratio (CR)
Population Size	50 individuals
Number of Generations	30
Number of Trials	10
Progress Monitoring	tqdm library
Best Tracking	tools.HallOfFame(1)

The setup of the Genetic Algorithm utilized in this investigation is described in Table 2. The DEAP library was used to implement the GA, and ten separate trials were conducted with a population of fifty individuals evolving over thirty generations. A progress meter was used to monitor optimization progress, and a Hall of Fame mechanism was used to identify the top performer from each run.

Table 3: GA Individual Setup and Evaluation

Component	Implementation
Individual Structure	List: [Speed, Load, Fuel, CR]
Fitness Function	FitnessMax (maximize BThEff)
Attribute Generation	Random values within bounds using <code>np.random.uniform()</code>
Population Init.	<code>tools.initCycle()</code> for individuals; <code>tools.initRepeat()</code> for population
Evaluation Function	Predict BThEff using trained surrogate model

For GA persons, the setup and evaluation procedure is summed up in Table 3. A list of four engine parameters was used to represent each individual, and a surrogate model that had been trained to predict BThEff was used to assess them. Randomly generated values within predetermined constraints were used to begin the population in order to guarantee a variety of legitimate candidate solutions.

Table 4: Genetic Operators and Constraints

Operator	Method	Details
Crossover	<code>tools.cxBlend(alpha=0.5)</code>	Blend crossover to mix parent genes
Mutation	<code>tools.mutGaussian(mu=0, sigma=50)</code>	Gaussian mutation with mutation prob. <code>indpb = 0.1</code>
Selection	<code>tools.selTournament(tourntsize=3)</code>	Best individual selected from randomly chosen subset
Bounds	<code>checkBounds</code> decorator	Clips values within: Speed (1400–1800), Load (0–90), Fuel (15–20), CR (16–17)

The boundary restrictions and genetic operators utilized in the GA implementation are shown in Table 4. Competition was maintained through tournament selection, while diversity was added by blend crossover and Gaussian mutation. All arguments were kept inside reasonable engine running limitations by using a bounds-checking decorator.

```
def eval_individual(ind):
```

```
    speed, load, fuel, cr = ind
```

```
    X = pd.DataFrame([[speed, load, fuel, cr]], columns=features)
```

```
    y_pred = model.predict(X)
```

```
return y_pred[0],
```

2.6 Statistical Analysis

To compare PSO and GA results, basic statistical methods were used. Mean BThEff values and 95% confidence intervals were calculated using the t-distribution. An independent t-test was conducted to check for significant differences between the two algorithms.

Table 6: Statistical test result

Method	Mean (%)	BThEff	95% Confidence Interval (%)	T-test p-value
PSO	30.05		(29.998, 30.097)	0.5684
GA	30.07		(30.012, 30.121)	

The statistical comparison of the GA and PSO optimization results is shown in Table 6. The t-test p-value of 0.5684 shows that although GA's mean BThEff (30.07%) was somewhat higher than PSO's (30.05%), the difference was not statistically significant. The 95% confidence ranges for both approaches overlapped, indicating similar performance.

3. Results and Discussion

3.1 Feature Importance

Engine load was found to be the most important factor by the Random Forest model, accounting for more than 50% of the variation in BThEff. Among the input parameters, engine speed had the least impact, followed by fuel blend ratio and compression ratio. This result validates the selection of these optimization parameters.

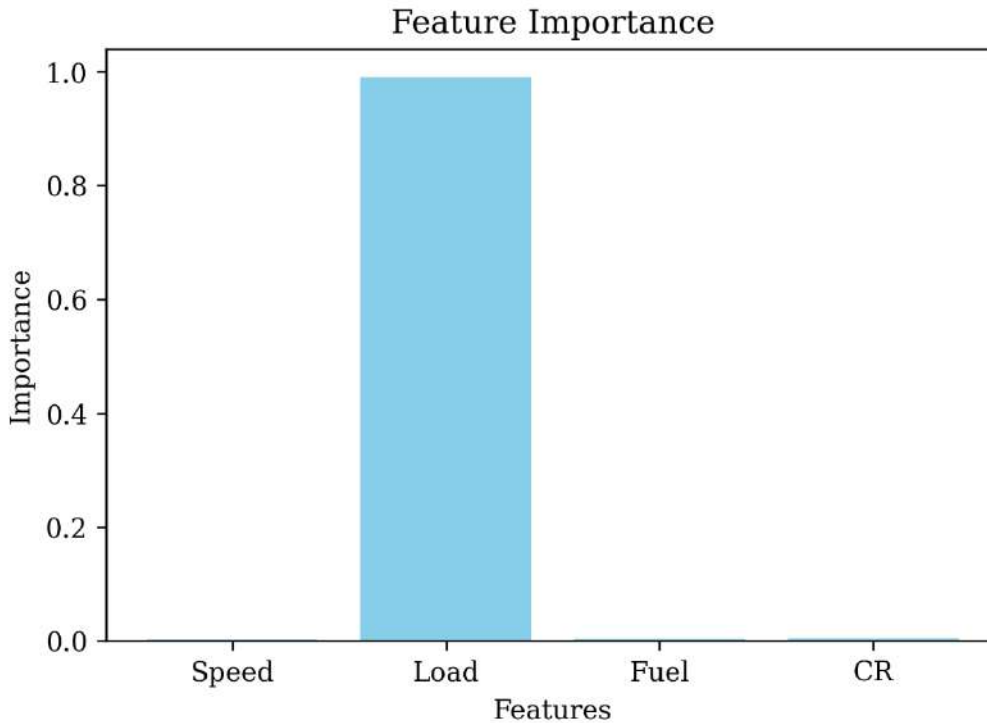


Figure 1. Feature importance plot from Random Forest model showing relative impact of engine parameters on BThEff.

The Random Forest model's feature importance is displayed in Figure 1. Engine load has the most influence on brake thermal efficiency out of all the input parameters; speed, fuel blend, and compression ratio have the least effect.

3.2 GA and PSO Optimization results

The best optimization outcomes utilizing PSO and GA are shown in Table 7. With a greater compression ratio and a lower fuel blend, GA's brake thermal efficiency (30.56%) was somewhat higher than PSO's (30.30%). Both approaches favored high-load conditions, underscoring their crucial role in optimizing engine performance.

Table 7. Best optimization result using PSO and GA.

	Speed	Load			BThEff
Method	(rpm)	(%)	Fuel (%)	CR	(%)
PSO	1416.744	90	19.53891	16.64148	30.2962

GA	1453.311	88.78947	17.33087	17.57565	30.5615
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GA performed consistently across trials, achieving a peak BThEff of **30.56%**. The algorithm favored a higher CR and slightly lower fuel blend than PSO.

Table 8. Multiple high-performing configurations from PSO and GA.

Method	Speed	Load	Fuel	CR	BThEff
PSO	1426.007	90	18.79076	17	30.1303
PSO	1425.664	90	16.12176	16.65138	30.1303
PSO	1694.516	89.37962	17.09765	16.80715	30.0679
PSO	1426.428	90	17.28998	17	30.1303
PSO	1426.019	90	16.76658	16.65599	30.1303
PSO	1800	90	20	16.84029	30.0679
PSO	1673.994	88.52089	15.5259	16.66644	30.0679
PSO	1429.327	90	16.60868	16.63904	30.0962
PSO	1425.933	87.53771	20	16.72853	30.1303
PSO	1427.525	90	19.11748	16.56528	30.1303
GA	1735.824	88.64889	15.41443	16.58593	30.0679
GA	1424.528	89.18583	16.41904	16.66526	30.1303
GA	1427.046	89.73242	18.74237	17	30.1303
GA	1440.923	89.43907	19.69166	16.60527	30.0802
GA	1427.81	90	16.5471	16.63489	30.1303
GA	1424.886	87.57301	15.52189	16.63502	30.1303
GA	1426.856	90	18.06544	16.62418	30.1303
GA	1425.538	90	16.94674	16.67793	30.1303
GA	1425.917	90	16.39172	16.84486	30.1303
GA	1426.398	88.43137	17.40038	16.51571	30.1303

Table 8 provides a list of several high-performing setups that were made possible by GA and PSO. Both approaches reliably found that moderate fuel blends and high engine loads (usually 87–90%) had the best brake thermal efficiency (BThEff > 30.13%). Effective optimization is accomplished across a variety of input parameters, according to the results, with a preference for compression ratios between 16.5 and 17.

3.3 Statistical Comparison

Both algorithms were statistically similar in performance. The average BThEff and 95% confidence intervals were:

- PSO: $30.0476 \pm 0.0498\%$
- GA: $30.0665 \pm 0.0543\%$

A t-test returned a p-value of **0.5684**, indicating no significant difference ($p > 0.05$).

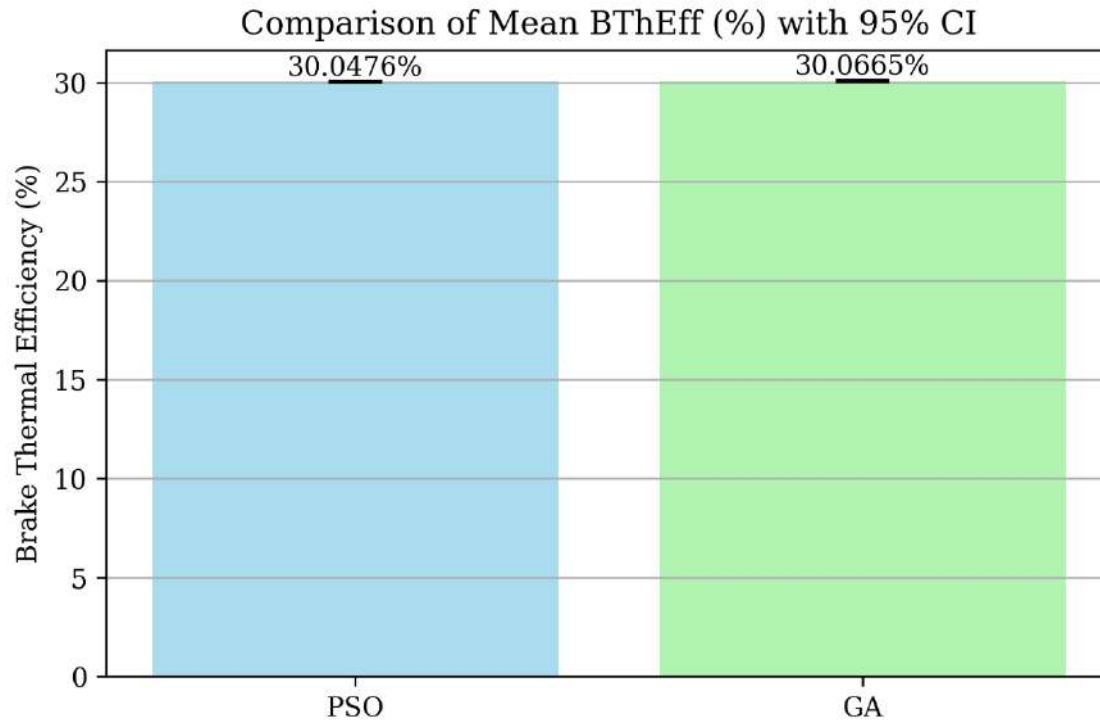


Figure 2. Bar plot comparing mean BThEff of PSO and GA with 95% CI.

Figure 2 displays the 95% confidence intervals for the mean brake thermal efficiency (BThEff) for GA and PSO. In comparison to PSO (30.0476%), GA's mean BThEff (30.0665%) was somewhat higher; nevertheless, the overlap of the confidence intervals suggests that there was no statistically significant difference. This lends credence to the finding that the two algorithms' performances were comparable

4. Validation

4.1 Bootstrap Validation

Bootstrap sampling ($n = 1000$) confirmed the robustness of the PSO results. The histogram showed mean BThEff centered near **30.02%** with low variation. Based on 1000 resampled means, the bootstrap distributions of mean BThEff for both PSO and GA are displayed in

Figure 3. A marginal performance benefit and increased consistency are indicated by GA's somewhat smaller distribution, which is skewed toward higher efficiency values. Bootstrap sampling (n=1000) validated PSO's resilience; the histogram's mean BThEff was centered at 30.02% with minimal fluctuation[23]. The densely grouped results from both approaches supported the surrogate-based optimization's dependability[24].

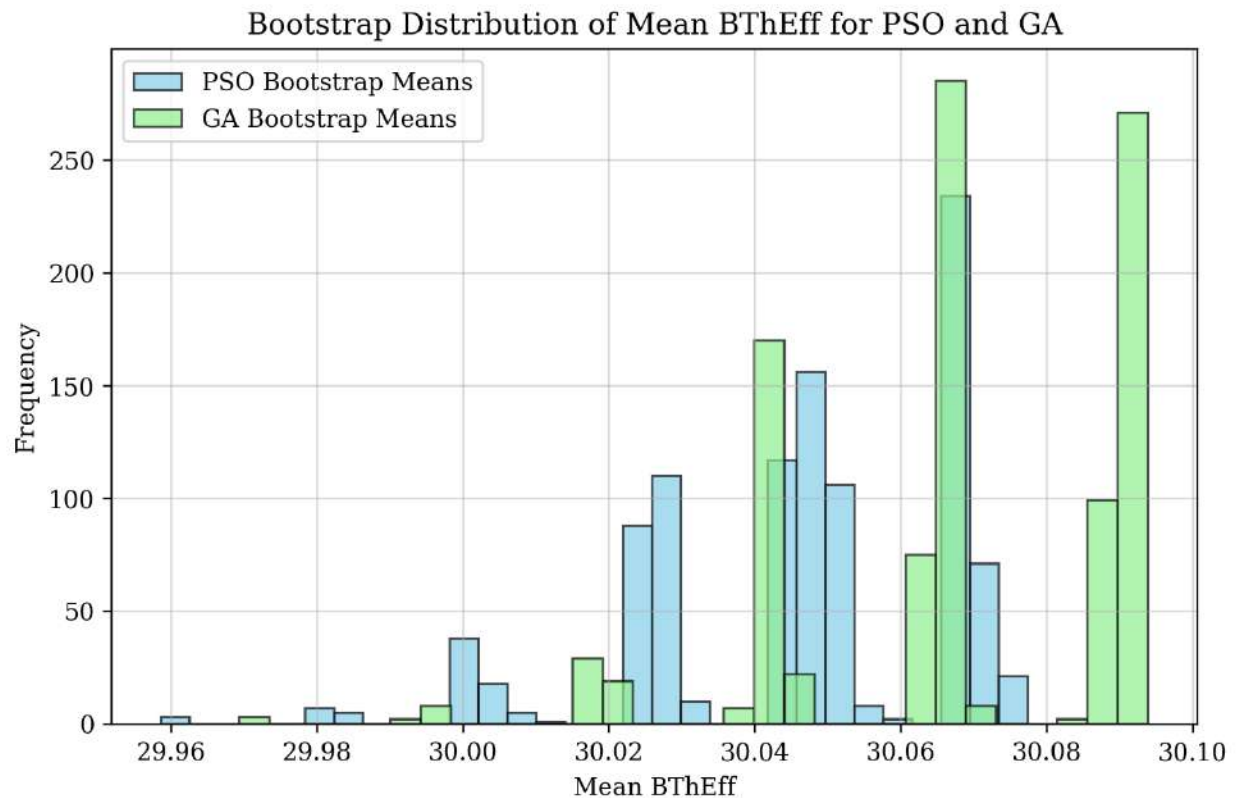


Figure 3. Bootstrap distribution of mean BThEff from PSO and GA trials.

4.2 Convergence Analysis

Convergence plots showed GA reached optimal values faster and with less variation. PSO also converged reliably but took longer.

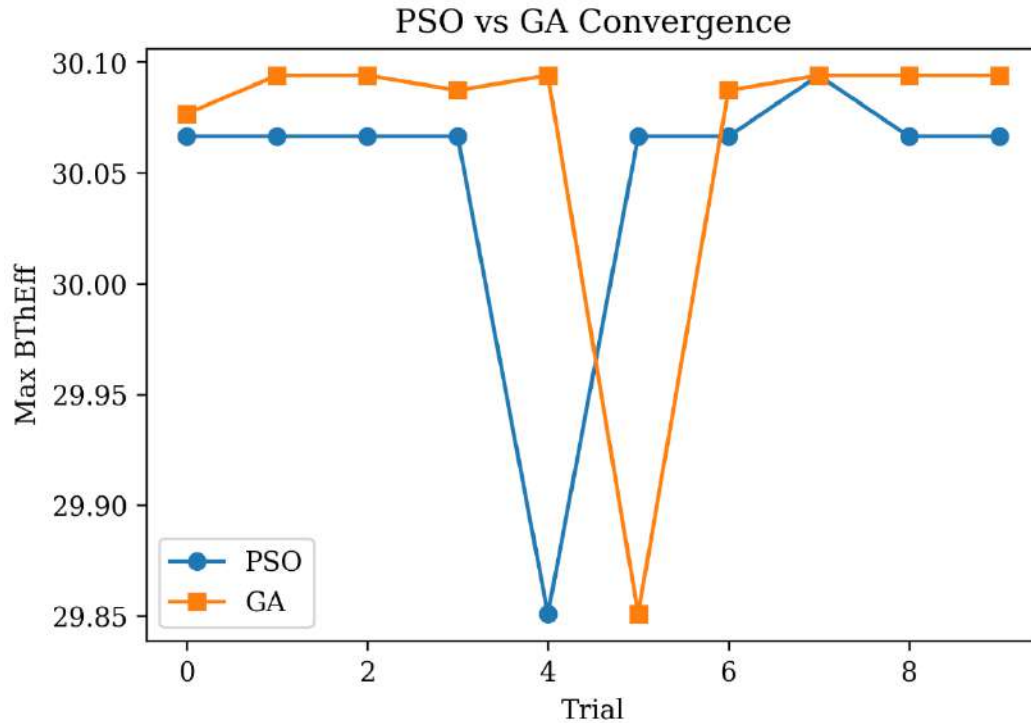


Figure 4. Convergence performance of PSO and GA across iterations.

PSO and GA's convergence behavior across ten separate trials is shown in Figure 4. With less variation in outcomes, GA consistently obtained greater BThEff in the majority of runs. Although both approaches exhibited occasional performance drops, GA demonstrated faster recovery and greater overall stability

Table 9. Computation time comparison between PSO and GA.

Optimization Method	Computation Time (seconds)	Efficiency Comparison
PSO	210.67	Slower
GA	133.68	Faster (36.5% reduction)

The computation times for PSO and GA are contrasted across optimization runs in Table 9. With an average time of 133.68 seconds, GA finished the optimization process much more quickly than PSO, which took 210.67 seconds. This demonstrates GA's greater efficiency by reducing computation time by 36.5%. [25]

4. Conclusion

This study showed how well Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) work to optimize the following diesel engine parameters for Karanja biodiesel: speed, load, fuel blend ratio, and compression ratio. Both algorithms produced brake thermal efficiency (BThEff) values above 30% using a Random Forest surrogate model. In contrast to PSO, which attained a maximum of 30.30% and an average of 30.05%, GA reached a maximum BThEff of 30.56% and an average of 30.07%. GA provided a 36.5% reduction in computation time (133.68 s) over PSO (210.67 s). Overlapping 95% CIs and statistical analysis ($p = 0.5684$) verified that there was no significant difference in performance. While PSO offered a wider range of solutions, GA demonstrated quicker convergence and more reliable outcomes. When combined with engine settings that are tuned, these results confirm that Karanja biodiesel is an effective alternative fuel. Future research should concentrate on real-time control techniques, experimental validation under changeable operating conditions, and multi-objective optimization that includes emissions. Future work should explore multi-objective optimization (including emissions), real-time implementation, and experimental validation of the predicted outcomes.

References:

- [1] M. Patel G. C., A. B. S., Jagadish, A. K. Shettigar, and O. D. Samuel, *Biofuel Production, Performance, and Emission Optimization*, vol. 215. Cham: Springer Nature Switzerland, 2025. doi: 10.1007/978-3-031-84806-3.
- [2] R. L. Krupakaran *et al.*, "Optimization and performance characteristics of low heat rejection engine powered by mahua bio diesel by Taguchi technique," *Mater Today Proc*, May 2023, doi: 10.1016/J.MATPR.2023.04.504.
- [3] R. Khujamberdiev and H. M. Cho, "Exploring the Environmental and Performance Implications of Utilizing Waste Swine Oil Biodiesel in CI Engines," *Energies (Basel)*, vol. 17, no. 3, p. 551, Jan. 2024, doi: 10.3390/en17030551.
- [4] N. K. Singh, Y. Singh, A. Sharma, and E. A. Rahim, "Prediction of performance and emission parameters of Kusum biodiesel based diesel engine using neuro-fuzzy techniques combined with genetic algorithm," *Fuel*, vol. 280, p. 118629, Nov. 2020, doi: 10.1016/J.FUEL.2020.118629.

- [5] M. Patel G. C., A. B. S., Jagadish, A. K. Shettigar, and O. D. Samuel, "Studies on Oil Extraction, Biodiesel Production Methods, and Engine Performance and Emission Characteristics," 2025, pp. 23–70. doi: 10.1007/978-3-031-84806-3_2.
- [6] A. Ahmad, A. K. Yadav, and A. Singh, "Modelling and optimisation of VCR diesel engine parameters fuelled with microalgae methyl-ester: a RSM-coupled Taguchi approach," *International Journal of Ambient Energy*, vol. 44, no. 1, pp. 2480–2488, Dec. 2023, doi: 10.1080/01430750.2023.2258373.
- [7] C. Tiwari, T. N. Verma, and G. Dwivedi, "Optimization of biodiesel production parameters for hybrid oil using RSM and ANN technique and its effect on engine performance, combustion, and emission characteristics," *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, Mar. 2024, doi: 10.1177/09544089241241130.
- [8] C. Tiwari, G. Dwivedi, and T. N. Verma, "Experimental study of diesel engine performance and emissions from microalgae fuel blends with SiO₂ nanoadditives: RSM and Taguchi optimization," *Environmental Science and Pollution Research*, Aug. 2024, doi: 10.1007/s11356-024-34724-6.
- [9] K. Kavalli, G. S. Hebbar, and A. Rout, "Application of Fuzzy-NSGA-II for achieving maximum biodiesel yield from waste cooking oil," *Environmental Science and Pollution Research*, Feb. 2025, doi: 10.1007/s11356-025-36079-y.
- [10] P. Kumar, A. K. Dhingra, D. Chhabra, and A. Chhikara, "Multi-objective Parameter Optimization of Four-Stroke Diesel Engine with Waste Cooking Oil Biodiesel and Diesel Blend using RSM-NSGA-II," *National Academy Science Letters*, vol. 47, no. 5, pp. 515–520, Oct. 2024, doi: 10.1007/s40009-023-01376-y.
- [11] A. Dewangan, A. Mallick, A. K. Yadav, A. Ahmad, D. Alqahtani, and S. Islam, "Combined Effect of Operating Parameters and Nanoparticles on the Performance of a Diesel Engine: Response Surface Methodology-Coupled Genetic Algorithm Approach," *ACS Omega*, vol. 8, no. 27, pp. 24586–24600, Jul. 2023, doi: 10.1021/acsomega.3c02782.
- [12] S. S. Selvan, P. S. Pandian, A. Subathira, and S. Saravanan, "*Saraca asoca* seeds – A novel candidature for biodiesel production: Studies on yield optimization using ANN coupled GA and properties of biodiesel blends," *Int J Green Energy*, vol. 15, no. 14–15, pp. 918–929, Dec. 2018, doi: 10.1080/15435075.2018.1529586.
- [13] C. Tiwari, T. N. Verma, and G. Dwivedi, "Optimization of biodiesel production parameters for hybrid oil using RSM and ANN technique and its effect on engine performance, combustion, and emission characteristics," *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, Mar. 2024, doi: 10.1177/09544089241241130.
- [14] S. K. Patidar and H. Raheman, "An AI-based approach to improve the fuel properties and performance of nano graphene added straight Karanja oil prepared with optimal dispersion

- parameters,” *Biofuels*, vol. 14, no. 6, pp. 619–633, Jul. 2023, doi: 10.1080/17597269.2022.2161130.
- [15] S. Chatterjee, “An experimental investigation on preparation and performances of two diesel blends of karanj oil methyl ester,” *International Journal of Oil, Gas and Coal Technology*, vol. 35, no. 4, pp. 442–475, 2024, doi: 10.1504/IJOGCT.2024.138687.
- [16] S. Mohan, P. Dinesha, and S. Bekal, “NO_x reduction of biodiesel engine using pongamia ester with oleic acid and optimization of operating conditions using particle swarm optimization,” *Int J Hydrogen Energy*, vol. 46, no. 52, pp. 26665–26676, Jul. 2021, doi: 10.1016/J.IJHYDENE.2021.05.124.
- [17] R. Kasimani, R. Sakthivel, D. Balasubramanian, J. S. Femilda Josephin, A. Chinnathambi, and E. G. Varuvel, “Response surface methodology optimization of characteristics of biodiesel powered diesel engine and its effective integration to autonomous microgrid,” *Process Safety and Environmental Protection*, vol. 189, pp. 1022–1036, Sep. 2024, doi: 10.1016/J.PSEP.2024.06.131.
- [18] S. Rami Reddy and S. K. Sarangi, “Optimizing the effect of using novel hydrogen enriched nano particles added emulsified waste mango seed biodiesel in diesel engine,” *Fuel*, vol. 342, p. 127783, Jun. 2023, doi: 10.1016/J.FUEL.2023.127783.
- [19] D. K. Bagal, A. K. Patra, S. Jeet, A. Barua, A. K. Pattanaik, and D. Patnaik, “MCDM Optimization of Karanja Biodiesel Powered CI Engine to Improve Performance Characteristics Using Super Hybrid Taguchi-Coupled WASPAS-GA, SA, PSO Method,” 2021, pp. 491–503. doi: 10.1007/978-981-16-0182-8_37.
- [20] V. V. Kannan *et al.*, “Artificial intelligence based prediction and multi-objective RSM optimization of tectona grandis biodiesel with Elaeocarpus Ganitrus,” *Sci Rep*, vol. 15, no. 1, p. 3833, Jan. 2025, doi: 10.1038/s41598-025-87640-1.
- [21] V. K. Viswanathan *et al.*, “Hybrid optimization and modelling of CI engine performance and emission characteristics of novel hybrid biodiesel blends,” *Renew Energy*, vol. 198, pp. 549–567, Oct. 2022, doi: 10.1016/J.RENENE.2022.08.008.
- [22] A. Ashok, S. K. Gugulothu, R. V. Reddy, A. E. Gurel, and B. Deepanraj, “Prediction-optimization of the influence of 1-pentanol/jatropha oil blends on RCCI engine characteristics using multi-objective response surface methodology,” *Renewable Energy Focus*, vol. 42, pp. 8–23, Sep. 2022, doi: 10.1016/J.REF.2022.05.006.
- [23] A. Coronado-Mendoza, M. Camas-Náfate, J. S. Artal-Sevil, and J. A. Domínguez-Navarro, “Optimum Design of a Photovoltaic Inverter System Based on Ga, Pso and Gwo Algorithms with a Mppt Sliding Mode Control,” *Energies (Basel)*, vol. 18, no. 8, p. 1911, Apr. 2025, doi: 10.3390/en18081911.

- [24] M. Alali, Z. Shahooei, and M. Bahramipanah, "Resiliency-Oriented Optimization of Critical Parameters in Multi Inverter-Fed Distributed Generation Systems," *Sustainability*, vol. 13, no. 12, p. 6699, Jun. 2021, doi: 10.3390/su13126699.
- [25] A. Abdulhussein Jabbar and A. Sabri Abd ALRazaq, "PSO vs GA: A Comparative Study of Multi-Objective Reliability Optimization using Fuzzy Nonlinear Programming Functions," *Wasit Journal for Pure sciences*, vol. 2, no. 2, pp. 143–149, Jun. 2023, doi: 10.31185/wjps.148.