

OPTIMIZATION OF PERFORMANCE PARAMETER OF IC ENGINE POWERED BY BLENDED KARANJA BIODIESELS WITH DISTINCT INJECTORS USING TAGUCHI-BASED HYBRID APPROACHES

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Abstract

Performance characteristics and emissions parameters of a Kirloskar diesel engine having single-cylinder compression ignition (CI) with direct injection (DI), water-cooled, running at 1500 rpm with variable load were tested in the blending percentage of Karanja methyl esters (KME) B10, B20, and B30 with diesel, the biodiesel made from Karanja oil, along with pure diesel. An experimental Taguchi L16 matrix is prepared for the analysis of performance, combustion, and emissions characteristics of the engine mentioned above with 3-hole, 4-hole, 5-hole, and 6-hole injection systems. Two hybrid methods are used for the optimization of engine parameters first one is the combination of Principal Component Analysis (PCA) and Utility method, and the other one is the combination of Criteria Importance through Criteria Inter-Correlation (CRITIC) and Utility method. The optimal factor level for higher brake thermal efficiency (BTE), lower brake-specific fuel consumption, and lower engine emission in blending conditions is achieved by having a fuel injector with a 6-hole nozzle in combination with a B20 blending condition at 60% loading condition. This optimal level condition provides higher BTE, lower SFC, and lower engine emissions compared to other conditions.

Keywords: Brake thermal efficiency (BTE); Criteria Inter-Correlation (CRITIC); Karanja methyl esters (KME); Principal Component Analysis (PCA); Taguchi L16; Utility method

Introduction

As a result of the current situation's ongoing and constrained petroleum supply in the current situation, prices of fossil fuels are rising (Majeed Khan *et al.*, 2023). This makes it necessary to discover alternative diesel fuels that may be used to power diesel engines. (Nair *et al.*, 2021). Vegetable

oils derived from plants, such as palm, jatropha, coconut, soybean, sunflower, and seed oils, can be used to make biodiesel. (Rajesh *et al.*, 2021). Because it is renewable and emits comparatively fewer emissions from the exhaust than traditional diesel fuels, such as diesel oil, biodiesel is regarded

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as an ecologically beneficial fuel. (Singh & Gupta, 2024). Furthermore, the fact that plants would reabsorb the exhaust gases generated during combustion and release them into the atmosphere for photosynthesis makes biodiesel recognized to be ecologically benign. (Mishra *et al.*, 2017). Exhaust emissions may be decreased with biodiesel without compromising engine efficiency or performance. (An *et al.*, 2013). The primary hindrance to the widespread use of biodiesel is its high cost. (Banapurmath *et al.*, 2012). This is evident from the fact that manufacturing biodiesel still costs 15.4% more than producing petroleum-based fuel. Various biomass that contains oil can be converted into biodiesel. (Nagesh, 2019). When utilized in stock diesel engines, biodiesel offers several advantages over diesel. By mixing, using, and creating biodiesel, there is a greater opportunity to minimize the amount of fossil fuel in a nation like India. (Anantha Padmanabha & Mohanty, 2024). The Indian government only allowed a 10% biodiesel blend, but this can easily be increased to 20% since most biodiesel blends with diesel operate best at 20% (Patel & Sankhavara, 2017).

Combustion characteristics of biodiesel have been widely investigated, with particular emphasis on ignition delay (ID) and heat release rate (HRR) due to their strong influence on engine performance and emissions. Most studies consistently report that biodiesel fuels exhibit a shorter ignition delay compared to mineral diesel. This trend is primarily attributed to biodiesel's higher cetane number, enhanced oxygen content, and greater chemical reactivity, which accelerate low-temperature oxidation reactions. Several researchers have also noted that the higher viscosity and density of biodiesel can slightly influence atomization, but these effects are generally outweighed by its high cetane rating. In terms of heat release rate, biodiesel combustion often shows a reduced premixed combustion phase when pure biodiesel is used, due to the shorter ignition delay, leaving less time for fuel-air mixing before ignition. However, biodiesel blends may exhibit a more pronounced premixed peak depending on blend ratio and operating conditions. The diffusion combustion phase for biodiesel is typically smoother and lower in magnitude, reflecting slower evaporation rates and the lower calorific value of biodiesel. The inherent oxygen content in biodiesel contributes to more complete combustion, which can shift HRR patterns and reduce soot-associated combustion phases.

The performance and emissions parameter analysis of CI engines making use of biodiesel as a fuel has been carried out via experimentation and testing (Gangil *et al.*, 2016). Researchers are thrilled about biodiesel as an alternative and sustainable

resource because of its higher cetane number, lower exhaust emissions, and flash point when compared to fossil diesel. (Chinwanitcharoen *et al.*, 2023). This section discusses the findings of some of the researchers who optimized one or more engine operating characteristics using blends of biodiesel and diesel or biodiesel alone. Anantha Padmanabha and Mohanty (2024) found that high injection pressure promotes the mixing of fuel with air in a better way, which enhances combustion process parameters and emission characteristics. They used the "Response Surface Method" to optimize engine process parameters and emission characteristics, and reported that engine process parameters and emission characteristics are improved when the same amount of fuel is injected near the main combustion chamber as opposed to when it is farther away. Brahma *et al.* (2022) assessed the impact of injection triggering (IT) on combustion process parameters and emission characteristics using diesel and renewable fuels like biodiesels and alcohol in diesel engines. They observed that while utilizing diesel fuel, advances in IT lower CO and HC emissions while increasing BTE and NO_x due to the rising temperature of exhaust gases. When diesel-biodiesel fuel mixes are used, IT retardation lowers NO_x emissions but increases HC and CO emissions. Verma *et al.* (2020) used biodiesel B20 blends from Roselle and Karanja in diesel and found that while BSFC and CO₂ increased in comparison to diesel, BTE, EGT, NO_x, and smoke decreased. Chauhan *et al.* (2013) compared the performance of diesel engines with different Karanja oil biodiesel blends and mineral diesel. In comparison to diesel, they discovered that while NO_x emissions are higher, BTE, CO, CO₂, and smoke are lower. Mahto *et al.* (2024) used response surface methods and artificial neural networks to optimize Karanja biodiesel using the Box-Behnken experimental design. Shrivastava *et al.* 's (2021) Investigation focused on energy, cost, and performance; biodiesel made from Karanja feedstock is a viable replacement for diesel fuel in CI engines. Anwar *et al.* (2023) Case-catalyzed transesterification method for producing biodiesel from local rapeseed oil was optimized. Baiju *et al.* (2009) produced biodiesel by employing both acid and alkaline catalysts in the methanolysis of inedible karanja oil. It was observed that the reaction conditions, which included a 1:10 oil/methanol molar ratio at 60°C, generated a methyl ester yield that was significantly lower (92%).

Based on the literature reviewed above, it can be concluded that while most researchers combined diesel and biodiesel, there haven't been many studies on optimizing the injector's hole count. Estimating engine operating characteristics, such as the injector's changeable nozzle hole count, is also

crucial. There is a dearth of research on the topic of optimizing the performance and minimizing emissions of a single-cylinder CI engine using three input parameters: loading conditions, nozzle hole count, and KME blending conditions. In the present work, optimization of performance, combustion, and emissions characteristics of a single cylinder CI engine with direct injection having diesel fuel and different blending portions of KME on diesel fuel has been done for 3-hole, 4-hole, 5-hole, and 6-hole injection systems using Taguchi L16 matrix and Pareto ANOVA analysis method. The optimum values for independent variables are found using multi-objective optimization, which aims to maximize performance parameters while minimizing emissions characteristics.

Materials and Methodology

Materials

Raw vegetable Karanja oil, 99.9% pure methanol (analytical grade), potassium hydroxide, and sulphuric acid were used in the preparation of Karanja methyl esters as a biodiesel. (Babu *et al.*, 2022). For the production of biodiesel, a two-liter capacity glass beaker, a heater that can control the temperature at a constant level, a mechanical stirrer with speed control, and a digital thermometer (Verma *et al.*, 2020). Diesel fuel was required for the preparation of different blending conditions along with KME. (Sinha & Murugavelh, 2016). Four sets of fuel injectors having 3-hole, 4-hole, 5-hole, and 6-hole nozzle systems were used to change

the injection opening condition. Table 1 shows the Detailed geometric specifications of test injectors used in this research study.

The hemispherical combustion chamber (HCC) was used in this research work; a line diagram for the HCC is shown in Figure 1. The schematic diagram for the four types of injector holes used in the experimental work is shown in Figure 2. The total opening area or total flow area of all injectors is approximately the same, so that the fuel amount of fuel injected in the combustion chamber is nearly the same.

For creating this precise dimensional profile, in injectors supplier uses the wire EDM machining process in different cases. All the holes are created evenly spaced about the angular symmetry and identically oriented as shown in Figure 2. All injector nozzles were fabricated with uniform circumferential symmetry and identical hole orientation to ensure consistent spray targeting and eliminate asymmetrical combustion effects. The injector was centrally mounted along the cylinder axis with identical orientation and protrusion for all tests, ensuring consistent spray targeting toward the piston bowl across all injector configurations. Figure 3 shows the close-up views of the injector nozzle tips with 3-, 4-, 5-, and 6-hole configurations, along with their respective hole diameters (0.28 mm, 0.24 mm, 0.22 mm, and 0.20 mm). The images confirm the uniform angular distribution and geometric consistency of the fabricated nozzles, which play a crucial role in influencing spray atomization, fuel-air mixing, and subsequent combustion characteristics.

Table 1. Detailed geometric specifications of test injectors

Injector Type	Number of Holes	Hole Diameter (mm)	Angular Spacing (°)	Total Flow Area (mm ²)	Spray Cone Angle (°)	Opening Pressure (bar)	Fabrication Method
Baseline (I1)	3	0.28	120	0.1847	150	180	Precision EDM
I2	4	0.24	90	0.1809	150	180	Precision EDM
I3	5	0.22	72	0.19	150	180	Precision EDM
I4	6	0.2	60	0.1885	150	180	Precision EDM

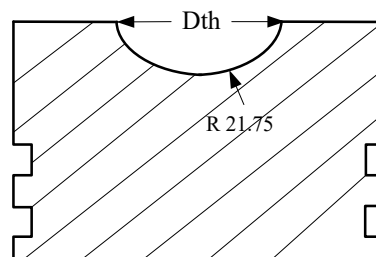


Figure 1. Line diagram of hemispherical combustion chamber (HCC)

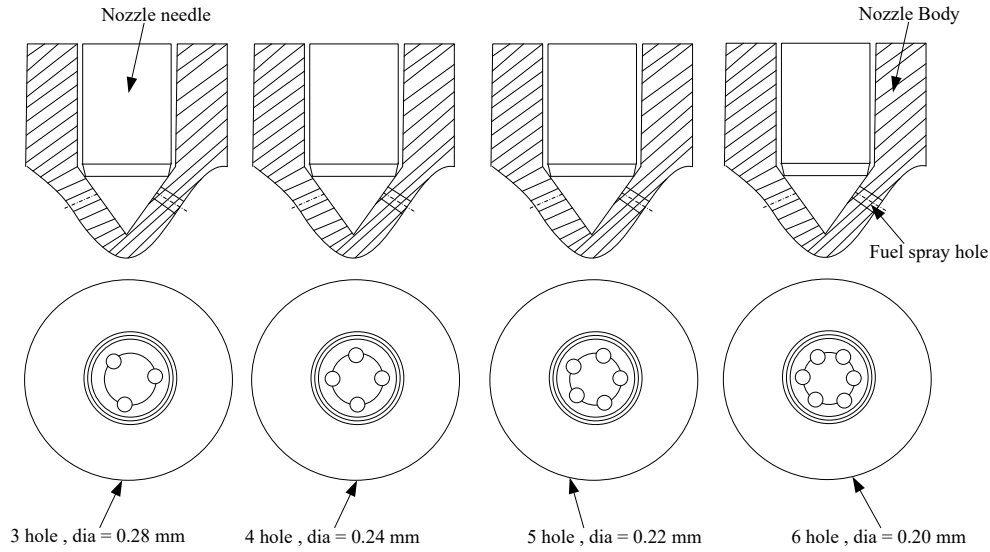


Figure 2. Schematic diagram for the four types of nozzle holes

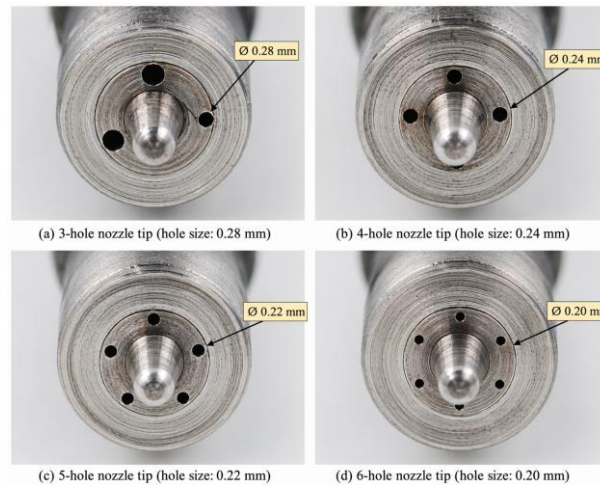


Figure 3. Image of different types of injectors

All injectors were calibrated to the same opening pressure, and engine load was controlled using the dynamometer under identical operating conditions. The fuel consumption rate was measured gravimetrically, and the variation in injected fuel mass among different injector configurations at a given load was found to be within $\pm 1\%$, which is within experimental uncertainty. This confirms that the injected fuel quantity remained comparable across all nozzles, and that the observed performance and emission differences are primarily due to spray distribution and atomization effects, rather than differences in fuel mass. The injector was centrally mounted with a fixed protrusion of 2.1 mm, and the spray cone angle was maintained at 150° for all configurations. The alignment and mounting geometry were kept

identical throughout the experiments to ensure that performance differences arose solely from changes in injector hole number and diameter, rather than positional variations.

Biodiesel Production

The steps carried out during the preparation of biodiesel are purification, transesterification, separation, and water wash. (Jatadhara *et al.*, 2023). In the purification step, raw vegetable Karanja oil is filtered and then heated to around 110°C in a closed container to remove the dirt, burned food, and water content in it, as shown in Figure 4 (Anantha Padmanabha & Mohanty, 2023). In the transesterification process, the oil is cooled to around 65 to 70°C and kept at this temperature for 25 minutes precisely. After that, a mixture is created

by adding purified Karanja vegetable oil of 1000 milliliters (ml), pure methanol of 250 ml, and potassium hydroxide of 25 grams. (Musthafa *et al.*, 2023). This prepared mixture is then swirled properly for an hour with the help of a mechanical stirrer, as shown in Figure 5 (Anwar *et al.*, 2023). In the separation step, the mixture is left for a day to settle in a separating flask, which separates glycerine and the esters, as shown in Figure 6

(Musthafa *et al.*, 2023). In the water wash step, after the biodiesel separates from the glycerine, it is dried, and then stored after being gently washed in slightly heated water to remove any leftover catalysts or soaps. (Anwar *et al.*, 2023). Now, KME is heated until the temperature reaches 110 °C to remove any leftover water, as shown in Figure 7 (Pawar *et al.*, 2023). Table 2 displays the properties of IS for Biodiesel, Diesel Fuel, and Karanja Methyl Esters.



Figure 4. Raw Karanja oil heated at 1100°C



Figure 6. Separation of glycerine from biodiesel



Figure 5. Karanja oil kept for reaction after mixing



Figure 7. Separation of biodiesel from water

Table 2. Properties of KME

Property	Diesel	KME	IS for Biodiesel
Specific gravity	0.85	0.876	0.86-0.90
Fire point (°c)	63	223	130
Flashpoint(°c)	56	217	120
Density (Kg/m ²)	836	885	860-900
Heating Value (KJ/Kg)	42800	36120	37270
Kinematic viscosity (c. stokes)	3.8	5.60	2.5-6

Taguchi L16

Taguchi L16 (4^3) created a way to design an experimental matrix to investigate the effects of various factor levels on the mean and variance of process parameters, which is a measure of process working performance (Mahto *et al.*, 2024; Mohammed *et al.*, 2019). By using this Taguchi L16 matrix, the total possible combination of 3 input parameters at four level from 64 to 16 only. Taguchi's proposed experimental design uses orthogonal arrays to arrange the process-affecting parameters and the levels at which they should be varied (Buchori *et al.*, 2019; Rajesh *et al.*, 2021; Jumaa & Mashkour, 2021). Unlike the factorial design, which requires testing every conceivable combination, the Taguchi technique tests pairs of possibilities (Kurniasih & Pardi, 2018; Sundar & Udayakumar, 2019; Yuliansyah *et al.*, 2019). The Taguchi L16 matrix is selected for the current research work, in which 4 levels are used for 3 variable parameters (Firdaus *et al.*, 2022; Rizal *et al.*, 2019). As suggested by Taguchi, the signal-to-noise (S/N) ratio is used for analysis and optimization. The highest S/N ratio is considered optimum when it corresponds to four response levels. The beak thermal efficiency should be high, whereas, from an economical and environmental perspective, the minimum values of BSFC and engine emission are highly desirable. For preparing the experimental matrix, three input parameters are selected in four different levels as per Table 3.

The experimental matrix is shown in Table 4.

To account for the inherent fluctuations in engine emissions, each emission parameter was measured after the engine reached steady-state operating conditions at the specified load and speed. Emission readings were recorded over a fixed sampling duration of 90 sec and the average of three consecutive readings was used for analysis. Prior to each test, the exhaust gas analyzer and smoke meter were allowed to warm up and were calibrated according to the manufacturer's recommendations.

Pareto ANOVA analysis method

Pareto ANOVA analysis represents a disproportionate improvement that can be achieved in the output performance parameters by ranking input variable parameters. The system can achieve better performance by concentrating on those input variable parameters with the largest impact. It is a technique for getting the most impactful variable. In the present work, for the first element (number of nozzle holes in injector), two levels were considered: one was 3 hole-nozzle, and the other was 5 hole-nozzle, for other elements, four levels were considered in the L16 experimental matrix with three input variables, which were selected for analysis of diesel engine performance characteristics and emission parameters.

Equations (1) and (2) demonstrate the computation of the signal-to-noise ratio (η_{ij}) of the

Table 3. Experiment input parameter levels

Input parameter	Level 1	Level 2	Level 3	Level 4
Number of Nozzle Holes (H)	3	4	5	6
Blending Condition (B)	Diesel	10K90D	20K80D	30K70D
% Loading (L)	20	40	60	80

Table 4. Taguchi L₁₆ experimental matrix

No.	H	B	L	Outputs				
	Number of Nozzle Holes	Blending Condition	% Loading	BTE (%)	BSFC (kg/kW-hr)	CO (% vol)	HC (ppm)	Smoke Opacity (%)
1	3 Holes	Diesel	20	11.82303	0.72137	0.11	33	4
2	3 Holes	10K90D	40	16.53784	0.5548	0.15	32	13
3	3 Holes	20K80D	60	21.45144	0.4384	0.2	28	15
4	3 Holes	30K70D	80	18.18622	0.52001	0.22	28	23
5	4 Holes	Diesel	40	17.49145	0.48759	0.17	37	15
6	4 Holes	10K90D	20	10.71764	0.8562	0.09	29	3
7	4 Holes	20K80D	80	21.60351	0.4353	0.24	31	25
8	4 Holes	30K70D	60	18.59049	0.5087	0.17	25	13
9	5 Holes	Diesel	60	22.96716	0.3713	0.21	37	18
10	5 Holes	10K90D	80	20.87141	0.4396	0.23	36	22
11	5 Holes	20K80D	20	11.74319	0.8008	0.09	23	2
12	5 Holes	30K70D	40	16.43205	0.5755	0.1	22	6
13	6 Holes	Diesel	80	26.32117	0.324	0.24	41	24
14	6 Holes	10K90D	60	20.32198	0.4515	0.19	31	16
15	6 Holes	20K80D	40	17.42802	0.5396	0.11	25	8
16	6 Holes	30K70D	20	10.3764	0.9114	0.07	19	1

j^{th} output for the i^{th} experimental runs to get LTB and HTB qualitative attributes; Equation (1) shows the signal-to-noise ratio for response with respect to the HTB qualitative attributes.

$$S/N_{\text{BTE}} = \eta_{ij} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{(y_{ij})^2} \right) \quad (1)$$

The response to the i^{th} trial's real experimental value is denoted by y_{ij} , and the word n refers to the number of tests. Equation (2) and (3) is utilised to compute the S/N ratio, which is indicative of the LTB quality attributes.

$$S/N_{\text{BSFC}} = \eta_{ij} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{(y_{ij})^2} \right) \quad (2)$$

$$S/N_{\text{CO, HC, Smoke}} = \eta_{ij} = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{(y_{ij})^2} \right) \quad (3)$$

PCA

PCA is the most frequently employed method for the exploration of multivariate data. The main objective of PCA is to use a reduced space, defined by variables known as principal components, that preserves the majority of the pertinent information from the original data in order to explain the variation in the original data. PCA provides eigenvectors and eigenvalues; these two parameters aid in the interpretation of the chemometric analysis of performance parameters. The eigenvectors, also known as loading vectors, provide information about the weighting function used to get the PCA scores, while the eigenvalues provide information about the variation in each PCA band. PCA initiates with the development of a multiple quality characteristics array as per the equation (4).

$$P_i(j) = \begin{bmatrix} P_1(1) & P_2(2) & \dots & P_1(n) \\ P_2(1) & P_2(2) & \dots & P_2(n) \\ \dots & \dots & \dots & \dots \\ P_m(1) & P_m(2) & \dots & P_m(n) \end{bmatrix} \quad (4)$$

In the current work, $P_i(j)$ represents the actual values of experiment number m (i.e., $m = 16$) with respect to performance parameters n (i.e., $n = 3$, CO emission as a single performance).

After the development of the above array, the coefficient of correlation is calculated according to equation (5).

$$Q_{j1} = \left(\frac{\text{Cov}(P_i(j), P_i(1))}{\sigma_{P_i(j)} \times \sigma_{P_i(1)}} \right) \quad (5)$$

The next step is to get the eigenvector and eigenvalues of the array developed with the coefficient of correlation using equation (6).

$$(Q - \lambda_k I_m) R_{ik} = 0 \quad (6)$$

Finally, principal components are calculated by using equation (7).

$$O_{mk} = \sum_{i=1}^n P_m(i) R_{ik} \quad (7)$$

CRITIC

The CRITIC method is used when researchers need clarity on the relative importance of different parameters that affect the system's performance. This method determined weights for the objective parameters. In order to facilitate decision-making in the case of a multi-objective function, the CRITIC approach eliminates the need for human intervention in the assessment process. In the CRITIC method, firstly, a decision matrix (D) is defined as in equation 8.

$$D = [d_{ij}]_{m \times n} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1m} \\ d_{21} & d_{22} & \dots & d_{2m} \\ \dots & \dots & \dots & \dots \\ d_{n1} & d_{n2} & \dots & d_{nm} \end{bmatrix} \quad (8)$$

In equation 1, 'n' represents the quality characteristics of the experimental design corresponding to the evaluation criteria, which is represented by 'm'. The i^{th} substitute of the output value for the j^{th} criterion is defined by d_{ij} .

The created decision matrix is normalized by using equation (9). To prevent numerical overflows between extremely big and small values of certain quality indicators, normalization is crucial.

$$\overline{d}_{ij} = \frac{d_{ij} - d_j^{\text{worst}}}{d_j^{\text{best}} - d_j^{\text{worst}}} \quad (9)$$

$$U(A_1, A_2, \dots, A_n) = f(U_1(A_1), U_2(A_2), \dots, U_n(A_n)) = \sum_{i=1}^n U_i(A_i) \quad (13)$$

$$U(A_1, A_2, \dots, A_n) = f(U_1(A_1), U_2(A_2), \dots, U_n(A_n)) = \sum_{i=1}^n W_i U_i(A_i) \quad (14)$$

In equation (9), the term $\bar{d}_{ij}$ represents the normalized response value of d_{ij} . d_{ij}^{best} and d_{ij}^{worst} , which denote the best and worst value of the j^{th} criterion.

The next step is to calculate the standard deviation (σ_j) of each vector d_j using equation (10).

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (\bar{d}_{ij} - \bar{d}_j)^2}{m}} \quad (10)$$

In equation (10), the number of experiments is referred to as 'm,' and the mean values of the j^{th} criteria are referred to as $\bar{d}_{ij}$.

After calculating the standard deviation by using equation (11), a symmetric matrix ($m \times m$) has to be developed using the linear correlation coefficient b/t d_j and d_k vectors represented by L_{jk} .

$$L_{jk} = \frac{\sum_{i=1}^m (\bar{d}_{ij} - \bar{d}_j)(\bar{d}_{ik} - \bar{d}_k)}{\sqrt{\sum_{i=1}^m (\bar{d}_{ij} - \bar{d}_j)^2 \sum_{i=1}^m (\bar{d}_{ik} - \bar{d}_k)^2}} \quad (11)$$

Finally, the weights of individual outputs are calculated using equation (12)

$$W_j = \frac{\sigma_j \sum_{k=1}^m 1 - r_{jk}}{\sum_{j=1}^n \sigma_j \sum_{k=1}^m 1 - r_{jk}} \quad (12)$$

Utility Concept

Utility, in general, describes how valuable a process or product is in relation to the degree of customer expectations by analysing their performances based on many discrete objective functions. In order to enhance logical decision-making, the many assessed or quality traits are combined to create a composite index or utility. The composite utility of the product is represented by the sum of the utilities of each characteristic. In accordance with utility theory, the variables i and n denote the number of objectives, while A_i stands for the attribute or output.

In equation (13), the i^{th} attribute of the utility is denoted by $U_i(A_i)$.

Applying weight fractions of every signal-to-noise ratio to a response that corresponds to each orthogonal array experiment run yields the multi-response S/N ratio in utility theory.

$\sum_{i=1}^n W_i = 1$ and the output i weight fractions are denoted by W_i in equation (14). Keep in mind that the total weight assigned to every output is set at 1. The quality attributes of the objective function that has to be optimized are better the greater the value of the utility function (Gaikwad *et al.*, 2020).

Experimental Program

A four-stroke, single-cylinder, constant-speed engine (Kirloskar, India) was utilized to collect the data for this investigation. This engine was designed for experiments because it included a variety of measuring and regulating tools. It was used for other agricultural tasks in addition to its experimental uses. The experimental single cylinder four-stroke CI engine setup is 5 BHP, having 110mm stroke length and 80 mm bore, 552.94 cc displaced volume, and a hydraulic loading condition. The setup has a 16.5: 1 comparison ratio with a 1500 rpm rated speed. Figure 8 shows this experimental setup with hydraulic loading. The exhaust emissions were measured using an AVL DiGas 444 exhaust gas analyzer, with measurement accuracies of $\pm 0.02\%$ vol for CO and ± 10 ppm for HC. This analyzer is capable of measuring NOx with an accuracy of $\pm 2\%$, but NOx data were not recorded during the experimental campaign for this study. Smoke opacity was measured using an AVL 437C smoke meter, with an accuracy of $\pm 1\%$ opacity.



Figure 8. Experimental setup

The engine's working fuel for the current project was biodiesel derived from Karanja seed oil. Because it is derived from an inedible oil, it is a second-generation biodiesel. It is created by using methanol and vegetable oil transesterification, with NaOH acting as a catalyst. Four distinct load settings—20%, 40%, 60%, and 80%—were used for the physical tests for the various mixes, which included B10, B20, and B30 with diesel. Diesel served as the benchmark fuel since it provides a good comparison for engine fuels in terms of the energy content to heat output ratio. The investigation proceeded to ascertain engine performance data for fuel injectors having 3-, 4-, 5-, and 6-hole nozzles for every fuel under consideration. The pressure of fuel injection is constant at 180 bars. 3-, 4-, 5-, and 6-hole nozzles have the same area of opening with a diameter shown in Table 1 correspondingly. The flow chart of the experiment is shown in Figure 9.

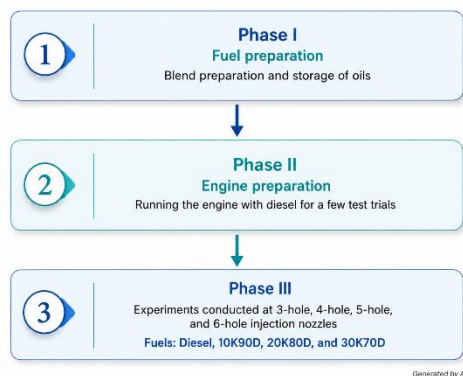


Figure 9. Experimental program

The experimental uncertainty was within $\pm 1.5\%$ for BTE, $\pm 2\%$ for BSFC, and $\pm 3\text{--}5\%$ for emission measurements, indicating good repeatability of the results. Emission measurements were analyzed in concentration units; however, conversion to mass-based emissions was not performed, which may influence comparisons across varying load conditions.

Results and Discussions

This section covers the experimental analysis of performance parameters and emission parameters for diesel engines in different operating conditions, and a discussion about the effect of these operating conditions on the performance and emission parameters of diesel engines based on experimental data gathered from the experiment. The performance and emission parameters of diesel engines are based on experimental data gathered from experiments. Previous studies have shown that biodiesel–diesel blends generally exhibit shorter ignition delay and reduced premixed heat release due to higher cetane number and oxygen content, which is consistent with the combustion trends observed in the present study. The in-cylinder pressure measurements were not performed, and therefore, detailed heat-release rate analysis could not be conducted in this study.

L16 Taguchi Experimental Matrix

The Taguchi method was chosen due to its ability to efficiently optimize multiple parameters with fewer experimental trials while ensuring robustness against experimental variability. Four levels were considered in the L16 experimental matrix with three input variables, which were selected for analysis of diesel engine performance characteristics and emission parameters. The three input variables, the first input variable is the number of holes in the fuel injector with the level of 3-, 4-, 5-, and 6-hole, the second input variable is the blending of Karanja biodiesel with diesel for the level of 100% diesel, 10% blending, 20% blending, and 30% blending, and the third input variable is loading condition with the level of 20%, 40%, 60%, and 80% of full load. The number of holes is represented by “N”, the blending percentage is represented by “B”, and the loading condition is represented by “L” in the paper. Table 5 shows the S/N ratio values for brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), carbon monoxide (CO), and hydrocarbon (HC) emissions with smoke opacity.

Table 5. Signal-to-Noise ratio for different parameters

Exp No.	Signal-to-Noise Ratio Value				
	BTE (dB)	BSFC (dB)	CO (dB)	HC (dB)	Smoke Opacity (dB)
1	21.45	2.84	19.17	-30.37	-12.04
2	24.37	5.12	16.48	-30.10	-22.28
3	26.63	7.16	13.98	-28.94	-23.52
4	25.19	5.68	13.15	-28.94	-27.23
5	24.86	6.24	15.39	-31.36	-23.52
6	20.60	1.35	20.92	-29.25	-9.54
7	26.69	7.22	12.40	-29.83	-27.96

Table 5. Signal-to-Noise ratio for different parameters (Continued)

Exp No.	Signal-to-Noise Ratio Value				
	BTE (dB)	BSFC (dB)	CO (dB)	HC (dB)	Smoke Opacity (dB)
8	25.39	5.87	15.39	-27.96	-22.28
9	27.22	8.61	13.56	-31.36	-25.11
10	26.39	7.14	12.77	-31.13	-26.85
11	21.40	1.93	20.92	-27.23	-6.02
12	24.31	4.80	20.00	-26.85	-15.56
13	28.41	9.79	12.40	-32.26	-27.60
14	26.16	6.91	14.42	-29.83	-24.08
15	24.82	5.36	19.17	-27.96	-18.06
16	20.32	0.81	23.10	-25.58	0.00

Examination of Diesel Engine Performance Parameters and Emission Parameters

A Pareto ANOVA was built for BTE, BSFC, CO, and HC emissions with smoke opacity by considering the calculated signal-to-noise ratio values of these parameters. Based on the analysis,

the percentage contribution of each element and the optimum values for each parameter were determined. Diesel fuel is considered the reference fuel for the analysis, so the optimum level is determined only in blending conditions (see Tables 6-10).

Table 6. Brake Thermal Efficiency based on Pareto ANOVA findings

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	97.65	101.94	83.77	195.18
	2	97.53	97.52	98.36	
	3	99.32	99.54	105.40	
	4	99.71	95.22	106.68	
The sum of squares of differences (SSD)		15.16	98.58	1325.59	1439.33
Percent contribution (PC)		1.05	6.85	92.12	100.00
Optimal levels (OL)		H ₄ B ₃ L ₄ (In blending conditions)			

Table 7. Brake-Specific Fuel Consumption based on Pareto ANOVA findings

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	20.80	27.47	6.92	41.48
	2	20.68	20.51	21.51	
	3	22.47	21.67	28.55	
	4	22.86	17.16	29.83	
The sum of squares of differences (SSD)		15.18	221.45	1325.82	1562.46
Percent contribution (PC)		0.97	14.17	84.85	100.00
Optimal levels (OL)		H ₄ B ₃ L ₄ (In blending conditions)			

Table 8. CO emission based on Pareto ANOVA findings

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	62.78	60.51	84.10	126.87
	2	64.09	64.58	71.04	
	3	67.24	66.46	57.35	
	4	69.09	71.64	50.71	
The sum of squares of differences (SSD)		99.68	255.87	2646.07	3001.62
Percent contribution (PC)		3.32	8.52	88.15	100.00
Optimal levels (OL)		H ₄ B ₄ L ₁			

Table 9. HC emission based on Pareto ANOVA findings

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	-118.36	-125.35	-112.43	-236.76
	2	-118.40	-120.30	-116.27	
	3	-116.57	-113.96	-118.09	
	4	-115.62	-109.33	-122.15	
The sum of squares of differences (SSD)		22.70	594.40	195.78	812.88
Percent contribution (PC)		2.79	73.12	24.09	100.00
Optimal levels (OL)		H ₄ B ₄ L ₁			

Table 10. Smoke Opacity based on Pareto ANOVA findings

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	-85.08	-88.27	-27.60	-168.38
	2	-83.30	-82.75	-79.43	
	3	-73.54	-75.56	-94.99	
	4	-69.75	-65.08	-109.65	
The sum of squares of differences (SSD)		664.64	1204.16	15327.28	17196.08
Percent contribution (PC)		3.87	7.00	89.13	100.00
Optimal levels (OL)		H ₄ B ₄ L ₁			

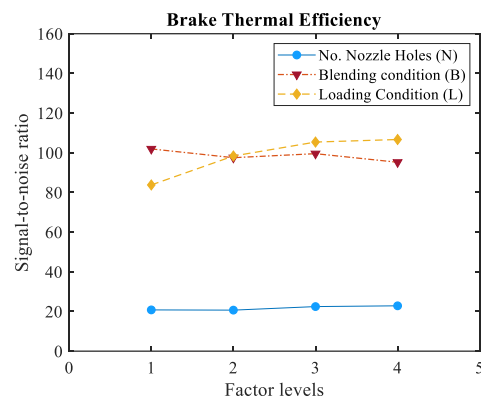
Performance Parameters

An engine's performance shows the efficiency with which the chemical energy included in fuel is transformed into useful mechanical work. An engine's performance parameters, like BTE, BSFC, CO, and HC emissions with smoke opacity, were examined during the present work. Responses to each performance parameter will be discussed in this section.

Brake Thermal Efficiency

The outcomes of the Pareto ANOVA are shown in Table 6 as the effect of all factor levels, optimum levels, and percent contribution corresponding to the response (i.e., BTE). In Figure 10, it is shown clearly that BTE is higher in the case of a nozzle having 6 holes as compared to a nozzle having 3 holes. Better atomization improves fuel-air mixing, enhancing combustion efficiency in the combustion chamber, which helps in the complete combustion of fuel. Brake Thermal Efficiency (BTE) increases with engine load due to reduced ignition delay and improved combustion efficiency at higher compression ratios. The 6-hole nozzle configuration enhances fuel atomization, leading to more complete combustion and higher BTE. The increased number of injection holes also leads to better spatial distribution of fuel within the combustion chamber, reduced spray penetration length, and improved utilization of available air. The combined effect of optimized hole diameter and higher hole count results in improved combustion characteristics, higher brake thermal efficiency, and reduced smoke emissions. It is observed from Figure 10 that different blends of Karanja methyl ester show slightly lower BTE as compared to diesel fuel. This is because of the low calorific value of Karanja methyl ester as compared to diesel fuel. 20% blending conditions have higher BTE as compared to other blending conditions because the optimum blending percentage of Karanja methyl ester with diesel fuel provides complete combustion of the charge, which significantly neglects the low calorific value of Karanja methyl ester. BTE decreases after 20% blending condition due to the higher percentage of Karanja methyl ester, which

has a lower calorific value. It is observed from Figure 10 that raising the engine running load leads to a rise in the brake thermal efficiency. BTE increases with engine load because improved combustion efficiency, higher in-cylinder temperatures, and a reduced proportion of heat and friction losses result in a greater fraction of fuel energy being converted into brake power. Note that engine loading condition (92.12%), followed by blending condition (6.85%), and number of holes in the nozzle (1.03%) produced the highest percentage impact on BTE. H4B3L4 is the optimum level of factoring to provide the optimal BTE in blending conditions.

**Figure 10. Response diagram for brake thermal efficiency**

Break-Specific Fuel Consumption

BSFC is a very important factor for engine running economy, which affects the overall performance of an engine. The three variables (i.e., number of holes in the nozzle, blending condition, and loading condition) effects on BSFC variations are presented in Figure 11. In Figure 11, it is noted that BSFC is less in the case of a nozzle having 6 holes as compared to a nozzle having 3 holes. BSFC decreases with increased load and improved nozzle design. The 6-hole nozzle, due to finer spray and better atomization, results in lower BSFC. Notably, the 20% KME blend at 80% load with a 6-hole nozzle shows an 18% reduction in BSFC compared to the 3-hole configuration. Because of this, proper

combustion of fuel has resulted in the BSFC being achieved. It is found in Figure 11 that different blends of Karanja methyl ester show slightly lower BSFC as compared to diesel fuel. This is because of the longer chemical chain in Karanja methyl ester as compared to diesel fuel. 20% blending conditions have better BSFC as compared to other blending conditions. BSFC decreases after 20% blending condition due to the higher percentage of Karanja methyl ester, which has a lower calorific value. It is observed from Figure 11 that raising the engine running load leads to a reduction in the BSFC. Note that engine loading condition (84.87%) followed by blending condition (14.18%) and number of holes in the nozzle (0.95%) produced the highest percentage impact on BSFC. H4B3L4 is the optimum level of factoring to provide the optimal BSFC in blending conditions after diesel. When comparing a nozzle having 6-holes for 80% loading condition with 20% blend fuel, the blending and loading condition BSFC is reduced by almost 18% that of a nozzle having 3-holes. As a result, the engine runs more economically in terms of BSFC when it is equipped with 6-hole nozzles and 20% Karanja methyl ester in the mixture at 80% loading condition.

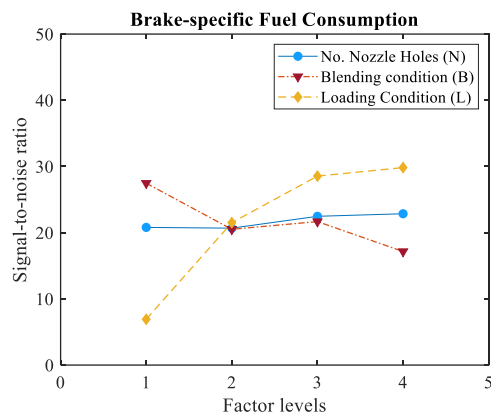


Figure 11. Response diagram for Break-Specific Fuel Consumption

Engine Emissions

CO Emission

CO emissions generally decrease with increasing load due to higher combustion temperatures, except at peak load, where fuel-rich conditions may lead to incomplete combustion. Biodiesel blends, especially 20% KME, show lower CO emissions than diesel due to their oxygenated nature, which promotes cleaner combustion. Figure 12 shows the variation of CO emission with different numbers of holes in the nozzle, blending condition, and loading condition. For all test blending conditions, it is noted that the CO emission declines with increasing loads and increases at the

highest load. This is because greater charge temperatures lead to better combustion at higher loads; nevertheless, incomplete combustion is caused by fuel richness at the highest load. The CO emission for blends 10%, 20%, and 30% are considerably lower than that of diesel. This is because blended fuels have more oxygen available for combustion, which improves combustion. The other explanation might be that plain oil and biodiesel have lower carbon-to-hydrogen ratios. But, for a blend of 10%, the CO emission is nearly similar to that of diesel. Note that engine loading condition (88.46%), followed by blending condition (8.55%), and the number of nozzle holes (2.99%) produced the highest percentage impact on CO emission. H4B4L1 is the optimum level of factoring to provide the optimal CO emission in blending conditions after diesel.

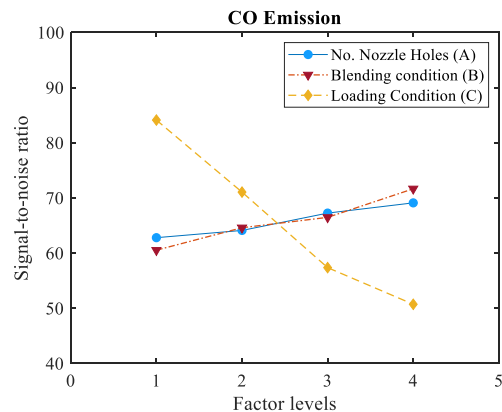


Figure 12. Response diagram for CO Emissions

HC Emissions

Hydrocarbon (HC) emissions are lower with higher KME blends due to the oxygen content in biodiesel, which facilitates more complete combustion. The 6-hole nozzle further reduces HC emissions by enhancing spray uniformity and turbulence. Figure 13 shows the variation of HC emission with different numbers of holes in the nozzle, blending condition, and loading condition. It is observed that a nozzle having a 6-hole releases less HC emissions than a nozzle having a 3-hole. This is due to better atomization and appropriate burning of fuel, with assistance from higher turbulence created in the case of 6-hole nozzles. With increased loads, the HC emission rises. Although higher loads generally reduce HC emissions, the present engine exhibited increased HC at high load due to over-fueling, locally rich combustion zones, and wall-wetting effects associated with increased injection quantity. HC emission reduces with the increasing blend percentage of Karanja methyl esters (KME) in fuel.

KME increases the engine efficiency of combustion and thus lowers HC emissions in the exhaust. This is due to KME having an oxygenated property. Note that the blending condition (73.29%), followed by the engine loading condition (24.14%) and the number of nozzle holes (2.57%), produced the highest percentage impact on HC emission. H4B4L1 is the optimum level of factoring to provide the optimal HC emission in blending conditions after diesel. When 20% blend fuel is used with 80% loading condition, the HC emission from a nozzle having 6-hole is over 3.5% less than that of a nozzle having 3-hole under the same blending and loading conditions.

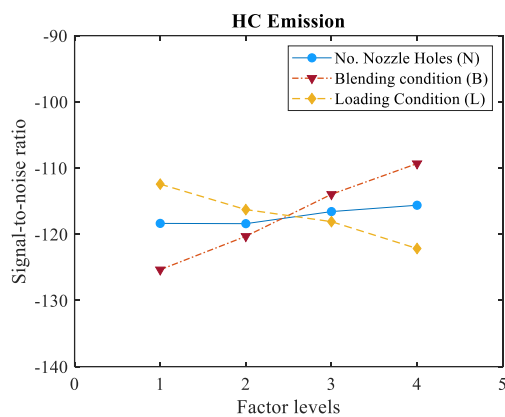


Figure 13. Response diagram for HC Emissions

Smoke Opacity

Smoke opacity decreases with higher KME blends and improved nozzle design. The 6-hole nozzle at 80% load with 20% KME blend shows a 25% reduction in smoke opacity compared to the 3-hole nozzle under similar conditions. Figure 14 shows the variation of smoke opacity with different numbers of holes in the nozzle, blending condition, and loading condition. It is observed that 6-hole nozzles smoke opacity is reduced compared to 3-hole nozzles. This is due to better atomization and appropriate burning of fuel with assistance from higher turbulence created in the case of 6-hole nozzles. With increased loads, the smoke opacity increases. Smoke opacity reduces with the increasing blend percentage of KME in fuel. KME increases the engine efficiency of combustion and thus lowers smoke opacity in the exhaust. This is due to KME having an oxygenated property. Note that engine loading condition (89.31%), followed by blending condition (7.02%), and the number of nozzle holes (3.67%) produced the highest percentage impact on smoke opacity. H4B4L1 is the

optimum level of factoring to provide the optimal smoke opacity in blending conditions after diesel. When 20% blend fuel is used with 80% loading condition, the smoke opacity value of a nozzle having 6-hole is 25% less than that of a nozzle having 3-hole under the same blending and loading conditions.

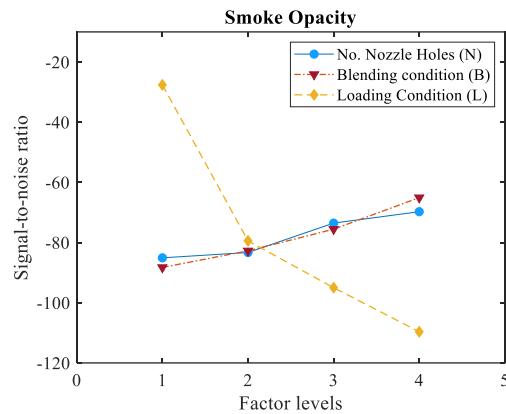


Figure 14. Response diagram for smoke opacity

Weight determination using PCA and CRITIC

In the PCA method, the correlation coefficient array is calculated using equation (5), and then the eigenvalues and eigenvectors are calculated using equation (6). Table 11 shows the eigenvalues and eigenvectors for different principal components.

Table 11. Weight determination using the PCA method

Eigen Value	PCs	Explained variation (%)	Cumulative proportion (%)
0.03	PC1	PC2	PC3
0.11	PC2	32.68	31.20
2.35	PC3	68.80	100

The weight fraction for each output is also determined via the CRITIC approach as an alternative to PCA. Taking into account each of the three parameters, the high value of BTE is considered a beneficial criterion to achieve high power output, and, in contrast, the low value of BSFC and CO emission is beneficial. The standard deviation values for each quality parameter, as determined by Equation (10), are also included in Table 12. Equation (12) is used to compute the weights of each output. The criteria data and the associated weights for each output are shown in Table 13.

Table 12. Normalized values of responses in the CRITIC method

Exp. No.	BTE	BSFC	CO Emission
1	0.091	0.324	0.765
2	0.386	0.607	0.529
3	0.695	0.805	0.235
4	0.490	0.666	0.118
5	0.446	0.722	0.412
6	0.021	0.094	0.882
7	0.704	0.811	0.000
8	0.515	0.686	0.412
9	0.790	0.919	0.176
10	0.658	0.803	0.059
11	0.086	0.188	0.882
12	0.380	0.572	0.824
13	1.000	1.000	0.000
14	0.624	0.783	0.294
15	0.442	0.633	0.765
16	0.000	0.000	1.000
SD	0.2918484	0.29593736	0.3498022

Table 13. Correlation coefficient, summation, and weights of different responses

	Correlation Coefficient			Summation of Responses			Weight of Response		
	BTE	BSFC	CO	BTE	BSFC	CO	Summation	C _j	W _j
BTE	1	0.130	0.0233	0	0.8695	0.9767	1.8462	0.5498	0.3470
BSFC	0.130	1	0.0529	0.8695	0	0.9471	1.8166	0.4859	0.3067
CO	0.023	0.053	1	0.9767	0.9471	0	1.9238	0.5485	0.3463

Utility Method

In terms of signal-to-noise ratio (S), the overall utility values are calculated using the utility technique according to equation (15).

$$S = S_1 W_1 + S_2 W_2 + S_3 W_3 \quad (15)$$

The signal-to-noise ratio of targets and related weight fractions of output parameters are denoted by the terms $S_1 W_1$, $S_2 W_2$, and $S_3 W_3$. Table 14 shows the weight fractions calculated using the PCA and CRITIC techniques.

Table 14. Different response weight fractions for PCA and CRITIC methods

Criteria	PCA	CRITIC
BTE. W1	0.4142	0.3343
BSFC. W2	0.2123	0.3243
TWR. W3	0.3734	0.3414

The signal-to-noise ratio is calculated using weight fractions determined by the PCA and CRITIC methods and by employing equation (15). Table 15 shows the values of the signal-to-noise ratio of two hybrid techniques, which combine the PCA method with the Utility approach and the CRITIC method with the Utility approach.

Table 15. S/N ratio of the two hybrid approaches

Criteria	S/N Ratio (PCA Utility Approach)	S/N Ratio (CRITIC Utility Approach)
1	14.458	15.926
2	15.356	15.671
3	16.014	15.316
4	14.758	14.198
5	15.550	15.456
6	14.226	16.325
7	15.546	14.491
8	15.608	15.493
9	16.566	15.557
10	15.534	14.602
11	14.693	16.642
12	16.362	17.483
13	16.996	15.478
14	15.910	15.389
15	16.459	17.283
16	14.649	17.312

Pareto ANOVA Findings Using PCA-Utility and CRITIC-Utility Approach

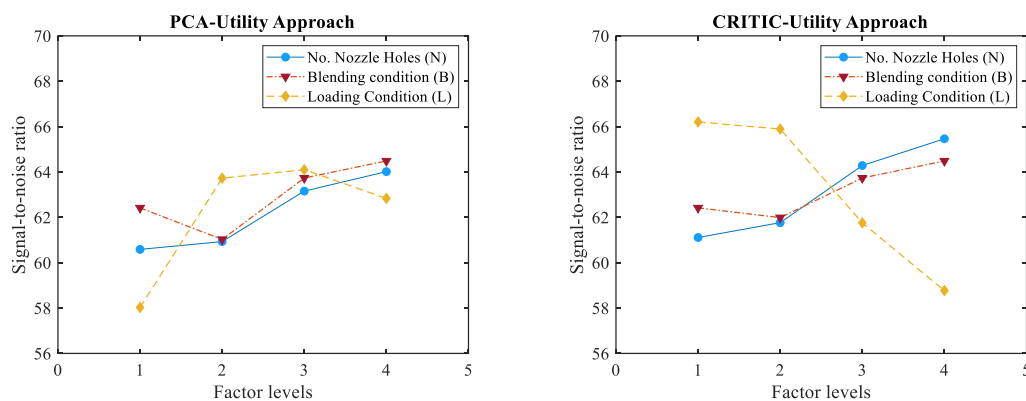
Pareto ANOVA is built for the signal-to-noise ratio calculated using the PCA-Utility and CRITIC-Utility approach. Table 16 shows the Pareto ANOVA findings in the case of the PCA-Utility approach. Table 17 shows the Pareto ANOVA findings in the case of the CRITIC-Utility approach.

Table 16. Pareto ANOVA findings for PCA-Utility approach

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	60.59	62.42	58.02	248.68
	2	60.93	61.03	63.73	
	3	63.15	64.48	64.10	
	4	64.01	63.73	62.83	
The sum of squares of differences (SSD)		33.67	27.80	95.06	156.53
Percent contribution (PC)		21.51	17.76	60.73	100.00
Optimal levels (OL)		H ₄ B ₃ L ₃			

Table 17. Pareto ANOVA findings for CRITIC-Utility approach

Factors	Levels	H	B	L	Total
Sum at factor levels (SFL)	1	61.11	62.42	66.20	252.62
	2	61.76	61.99	65.89	
	3	64.28	63.73	61.76	
	4	65.46	64.48	58.77	
The sum of squares of differences (SSD)		50.85	16.05	151.99	218.88
Percent contribution (PC)		23.23	7.33	69.44	100.00
Optimal levels (OL)		H ₄ B ₄ L ₁			

**Figure 15. Pareto ANOVA response for: (a) PCA-Utility approach, (b) CRITIC-Utility approach**

The percentage contribution of each element and the optimum levels for each outcome were calculated from the analysis.

To determine the optimum parameters, two hybrid methods combine PCA and CRITIC methods with the Utility approach. In both methods, the weight fraction is determined for each parameter. The weight fractions of these hybrid methods are different for every performance parameter. After preparing the Pareto ANOVA for these hybrid methods, the optimal levels are different in both cases. In the case of the PCA-Utility approach, the optimal level is H₄B₃L₃, and for the CRITIC-Utility approach, the optimal level is H₄B₄L₁.

While both PCA-Utility and CRITIC-Utility approaches identify optimal conditions, PCA-Utility offers clearer differentiation of performance parameters due to its emphasis on explained variance, as shown in Figure 15. The optimal condition H₄B₃L₃ (6-hole nozzle, 20% KME blend,

60% load) consistently yields superior performance and lower emissions

Conclusions

The use of non-edible Karanja biodiesel blends presents both environmental benefits through reduced emissions and economic advantages due to local availability and renewable sourcing. In the present work, optimization of performance, combustion, and emissions characteristics of a single cylinder CI engine with direct injection having diesel fuel and different blending portions of KME on diesel fuel has been done for 3-hole, 4-hole, 5-hole, and 6-hole injection systems using Taguchi L16 matrix and Pareto ANOVA for two hybrid methods. The following conclusions are drawn:

1. Loading condition is found to be the most dominating factor for higher BTE, lower BSFC, and lower engine emission compared to other factors.

2. The higher BTE, lower BSFC, and optimal engine emission are attained for 20% blending, 6-hole nozzle, and 60% loading condition.

3. The optimal conditions for both the hybrid methods are different. For the PCA-utility approach, the optimal condition is H4B3L3, and in the case of CRITIC-Utility approach, the optimal condition is H4B4L1. The optimal conditions found in both the approaches are analyzed, and it is found that the PCA-Utility approach provides the better and clearer optimal condition as H4B3L3 (20% blending, 6-hole nozzle and, 60% loading condition).

4. The result shows that the PCA-Utility approach is considered the better model to optimize the multi-responses in the case of an IC engine powered with blended fuel.

However, the emission analysis and optimization in the present study are based on concentration units (ppm/% vol.), which do not account for variations in exhaust mass flow across different engine loads and are therefore acknowledged as a limitation. The Taguchi S/N ratio approach remains valid as it evaluates relative performance robustness under identical operating conditions, enabling consistent comparison of parameter effects. In addition, although the exhaust gas analyzer (AVL DiGas 444) is capable of measuring NO_x emissions, NO_x data were not recorded during the experimental campaign; consequently, the emission analysis is limited to CO, HC, and smoke. Future work will focus on incorporating mass-based emissions (g/kWh) and comprehensive NO_x measurements to enable a more complete and rigorous environmental assessment.

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Author Contributions

Vishnu Singh: Conceptualization, Methodology, Investigation, Writing – Original Draft, Formal Analysis,.

Vikas Kumar Choubey: Supervision, Project Administration.

Vikas Upadhyay: Writing – Review & Editing, Manuscript Review.

Ethics Approval and Consent to Participate

Not applicable. This study did not involve human participants, human data, animals, or biological samples; therefore, ethics approval and consent to participate were not required.

Declaration of Generative AI

The authors declare that no Generative AI tools were used in the preparation of this manuscript.

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