THE TECHNIQUE PERFORMANCE EVALUATION AND EMISSION CHARACTERISTICS OF DIESEL, CERIUM OXIDE, AND ETHANOL

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Abstract

The engine performance and emission characteristics of diesel, cerium oxide, and diesel combined with ethanol were examined on a variable compression diesel engine. In order to discover the best process response with a limited number of trial runs, the Taguchi method and grey relational analysis were utilized to address the problem. Using the grey relational grade and signal-to-noise ratio as performance indices, it was anticipated that a specific set of input parameters would result in the best response characteristics. It was discovered that 50% of the mixture works well in a diesel engine without dramatically altering its emissions and performance characteristics.

Keywords: Biodiesel, VCR diesel engine, CI Engine, Taguchi, ANOVA, GRA

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1. Introduction

The use of alternative fuels has increased recently as a result of growing concerns about the depletion of fossil fuel resources and environmental issues including air pollution and climate change. Biodiesel and ethanol methyl ester (EME), two well-known alternative fuels that have drawn a lot of attention and offer a number of benefits over conventional diesel fuel. Utilized cooking oil, animal fats, and vegetable oils are just a few of the ingredients that can be utilized to make biodiesel, a renewable fuel. It has a lower carbon footprint than regular diesel and is biodegradable and non-toxic. A renewable fuel derived from agricultural products like corn and sugarcane, on the other hand, is ethanol. It is regularly added to petrol as well as utilized as a stand-alone fuel in flex-fuel cars. It depends on the performance and emission characteristics of biodiesel and EME to what extent their use in internal combustion engines is practical. It's critical to compare alternative fuels' power output, fuel consumption, and combustion characteristics to those of conventional diesel fuel when assessing their performance. The performance of biodiesel and EME in compression ignition (CI) engines has been investigated in a variety of trials. These investigations have revealed a range of results, depending on the fuel type, the engine type, and the running conditions. Biodiesel has been discovered to have a higher cetane rating, a lower calorific value, and a lower viscosity than diesel fuel. This result in decreased engine power output and increased fuel consumption because biodiesel has a longer ignition delay and a lower energy density. EME has a higher calorific value and lower viscosity than biodiesel, which boosts engine power and cuts down on fuel use. However, the lower cetane number and higher oxygen content of EME might lead to increased NOx emissions and engine deposits. The emission characteristics of alternative fuels are crucial in assessing their performance. Diesel engines emit hazardous pollutants like particulate matter (PM), nitrogen oxides (NOx), carbon monoxide (CO), and hydrocarbons (HC), which are harmful to both human health and the environment. Utilizing alternative fuels could help to reduce these emissions and improve air quality. Numerous studies have looked into the emission properties of biodiesel and EME in CI engines. It has been discovered that biodiesel can cut PM emissions by up to 60%, CO emissions by up to 50%, and HC emissions by up to 70% when compared to diesel fuel. Biodiesel can, however, increase NOx emissions due to its higher oxygen content and lower flame temperature. EME has been shown to lower CO, PM, and HC emissions by up to 60%, 90%, and 70%, respectively, when compared to diesel fuel. EME, however, has the potential to produce more NOx emissions because of its increased oxygen concentration. The performance and emission characteristics of biodiesel and EME are often affected by factors including the kind of fuel, engine, and operating conditions. Although the use of alternative fuels may reduce emissions and improve air quality, it is crucial to carefully consider the performance trade-offs involved. It is crucial to assess the technique performance evaluation and emission characteristics of biodiesel and EME in CI engines in order to produce sustainable and efficient alternative fuels.

Carraretto et al. [1] studied a CI engine first on a test bench and subsequently on a city bus. They discovered that the use of biodiesel increased nitrogen oxide (NOx) emissions as well as the consumption of specific fuels. However, there were less carbon dioxide and carbon monoxide emissions. Raheman et al. [2] suggested that diesel methyl ester made from karanja oil would be a suitable substitute fuel.

Their emission analyses revealed a considerable decrease in CO and NOx compared to diesel. Agarwal et al. [3] employed Ratanjyot (Jatropha), Karanja, Nagchampa, and Rubber to produce biodiesel utilizing methyl and ethyl alcohol. He added that because biodiesel doesn't require engine modification, it would be a better choice than petroleum diesel. Raheman and Ghadge [4, 5] conducted an experiment on a Ricardo E6 engine using Mahua biodiesel and its blends. The compression ratio was raised from 18 to 20. It was shown that higher biodiesel concentration increased brake-specific fuel consumption while brake thermal efficiency decreased. Research by Rao et al. [6] indicates that vegetable oils are suitable substitute fuels for agricultural diesel engines. The ability of these vegetable oils to increase smoke emissions was just about enough. Kalbande et al. [7] conducted research on the efficacy of diesel blends using biodiesel produced from karanja and jatropha. The findings indicated that B20 (20% biodiesel and 80% diesel) and B40 (40% biodiesel and 60% diesel) were the two blends with the highest Karanja biodiesel efficiency. In B60 and B80, jatropha yields were higher. Fontaras et al. [8] investigated the combustion and emission characteristics of biodiesel in a diesel passenger automobile that used soybean biodiesel and satisfied the EURO 2 emission standard. They discovered that the use of soy biodiesel had made cold starting more challenging. Godiganur et al. [9] claim that Mahua oil exhibited traits resembling those of diesel after trans-esterification. It was discovered that the blend with 20% (B 20) worked best. Baiju et al. [10] used Karanja oil to make methyl ester and ethyl ester. Both of them demonstrated acceptable emission characteristics, with the exception of the fact that the levels of NOx present were on the higher side. Furthermore, they asserted that methyl ester performed better than ethyl ester. Sahoo et al. [11], diesel was mixed with plant methyl esters from jatropha, karanja, and polanga. Using a B-50 blend, the strongest output was produced. It has been shown that using biodiesel to its fullest extent lowers smoke emissions. Compared to diesel emissions, CO and NOx emissions scarcely increased. Murugesan et al. [12] claim that the methyl ester of Karanja oil can be used in CI engines right away without modification. It was discovered that biodiesel had different emission characteristics and that brakes used more fuel than diesel. They deem the B 20 Blend to be the best diesel substitute. Duraisamy et al. [13] conducted a study using the methyl esters of Jatropha, Pongamia, Mahua, and Neem seed oil. B 40 biodiesel had a thermal efficiency that was nearly on par with diesel during engine performance tests. According to the results of an emission analysis, NOx and smoke density increased but carbon monoxide (CO) and hydrocarbons (HC) were reduced at any proportion mix.

The review of the literature made it plainly clear that researchers had worked diligently to find the best diesel fuel substitute that didn't necessitate major engine modifications. They typically adjusted the Engine Load, Ignition Pressure and Ignition timing respectively while monitoring how the engine operated and emitted emissions. It should be emphasized that there were multiple input parameters and that the system's response was not one-way. To put it another way, some responses had higher values that were preferable, whilst others had lower values that were. The study was consequently changed into a multi response optimization problem that required a rigorous methodology to ascertain how many tests would be required to cover the entire range of input parameters. In an effort to maximize reaction characteristics, the best set of input parameters were sought after using the data shown above. The experiment was designed to produce the most quantity of data with the fewest number of experiments. In this inquiry, biodiesel was used as an experimental fuel. The performance of biodiesel was evaluated on a Kirloskar engine with a single cylinder and variable compression ratio. The aim of the study was to determine the optimal diesel and cerium oxide and ethanol blend for engine performance and emissions production. According to the Grey-Taguchi method, a multi response problem was condensed into a single problem using the weighting factors of grey relational analysis. Finally, the results were verified through actual experimentation.

2. Methodology

A variable compression ignition engine's performance and emission characteristics can be improved by finding the appropriate blend of diesel, cerium oxide, and ethanol. The main design factors were considered to be three key input parameters: engine load, ignition pressure, and ignition timing. As seen in Table 1, there were five more layers created for each constituent. The levels and their ranges were decided upon in accordance with earlier findings that had been made public in the open literature. The performance parameters of the engine were related to brake pressure (BP), brake-specific fuel consumption (BSFC), and brake thermal efficiency (BTE). The following five responses, specifically CO, CO_2, O_2, NO_x, and HC, dealt with the engine's emission characteristics. Tests on the critical characteristics of ethanol, diesel, and cerium oxide fuels were performed in accordance with ASTM standards.

Table 1 Setting levels for design parameters

Controlled factors	**Level 1**	**Level 2**	**Level 3**
Engine Load (%)	30	60	90
Ignition Pressure(bar)	200	220	240
Ignition timing (BTDC)	20	22	24

There were so many input and output variables that it required multiple experiments to cover the entire area. A well-designed experiment could produce far more data with fewer runs than an unplanned experiment. Taguchi's parameter design method was used to analyze how different input parameters impact response. However, the conventional Taguchi method could successfully identify the ideal parameter choices for a specific performance feature. The Grey-Taguchi method was employed to integrate the many performance characteristics into a single response since there was multiple performance characteristics present with competing goals.

2.1 Taguchi Analysis.

By employing a robust test design, Dr. Taguchi's Taguchi technique sought to minimize process variation. A standard orthogonal array could be used to construct the experimental design depending on the overall number of degrees of freedom, the number of components, and the level of each component. An orthogonal array with 3 columns of input parameters, each with 3 levels, and 9 experiment rows, or the total number of tests, was used in the current inquiry.

2.1.1 Grey Relational Analysis.

The signal-to-noise ratio (S/N) measurement is a tool used by scientists and engineers to determine the ratio of the amount of a desired signal to the amount of background noise. A lower S/N ratio for another performance characteristic may be shown by the greater S/N ratio for one performance feature because the current study intended to maximize six response characteristics. Therefore, a comprehensive analysis of the S/N ratio was needed in order to optimize several performance-related factors. In order to effectively study this kind of issue, grey relational analysis was proven to be a useful method. It was used to determine the key elements of the system and how they relate to one another. The order of the input and output showed which parameters were essential. In the current study, experimental data were initially normalized in the range of zero to one. Then, using normalized experimental data, the relationship between the desired and actual experimental data was described using the grey relationship coefficients. The total grey relational grade was then calculated by averaging the grey relational coefficients for each selected process response. The evaluation of the multiple process response was built on the basis of the grey relational grade. This method was used to convert a multiple response process optimization problem into a single response problem using the objective function of overall grey relational grade. The level of parametric combination with the highest grey relational grade was shown to be the best process parameter. The original sequence was normalized as follows because the desired value was "the higher-the-better".

$$a^{*}(k) = \frac{a^{i}(k) - \min a^{i}(k)}{\max a^{i}(k) - \min a^{i}(k)} \qquad (1)$$

The original order was normalized as follows when "the lower-the-better" was the desired outcome.

$$a^{*}(k) = \frac{\max a^{i} - a^{i}(k)}{\max a^{i}(k) - \min a^{i}(k)} \qquad (2)$$

The starting reference sequence is denoted by yi(k), the comparison sequence is denoted by xi(k), and the total number of experiments and responses is indicated by i = 1, 2,..., m, and k = 1, 2, 3,..., n. From lowest to highest, the values of yi(k) are min yi(k) and max yi(k).

In this instance, xi(k) was the value that followed the grey relational creation. The ideal series was x0(k). The grey relational grade represented the degree to which the experimental run sequences [x0(k) and xi(k), i = 1, 2,..., m] were connected.
The grey relational coefficient i(k) could be calculated as

$$\varepsilon(k) = \frac{\Delta_{min} + \gamma\, \Delta_{max}}{\Delta_{o}\,(k) + \gamma\, \Delta_{max}} \qquad (3)$$

$$\Delta_{i}(k) = [x_{o}(l) - x_{i}(l)] \qquad (4)$$

It was the difference between the absolute values of x0(k) and xi(k). The min and max values, respectively, represent the absolute differences (0i) of each comparison series. The distinguishing coefficient (0-1) was developed to lessen the maximum effect's effects when they become too strong. For the sake of this inquiry, was set to have a value of 0.5. The grey relational coefficients were averaged to determine the grey relational grade o.

The value of the grey relational grade was considered to increase with the strength of the relationship between the ideal sequence x0(k) and the real sequence xi(k). The ideal sequence x0(k) was predicted to represent the ideal process response in the experimental design. The higher the relationship grade shown, the closer to the ideal the relevant parameter combination was.

2.2. Grey Relational Grade Generation
As the fuel blend was raised, engine performance showed a propensity to decrease, whilst emission characteristics indicated a tendency to increase. The analysis was done in a way that the engine performance wouldn't be adversely affected even when diesel was replaced with a mixture of ethanol, diesel, and cerium oxide because various external equipment types, including exhaust gas recirculation (EGR), can lower engine emissions. Engine performance was therefore given a greater weighting factor than emission criteria when converting several grey relation grades. When appropriate, weighting factors were used with the sequence values, and the overall format of the grey relationship grades altered.

$$y_i = \frac{1}{n}\sum_{k=1}^{n} \in_i (k) \quad (5)$$

The distinct sequence value of the weighting component may be provided by experience, or suitable weights may be produced using strategies like singular value decomposition and preliminary grey relational grading values. It should be noted that using weighting factors would not be equivalent to changing the sequence value units used or choosing to utilize sequence normalization.

Experimental Set up
The engine was immediately connected to an eddy current dynamometer via a flexible connector (Figure 1). The output of the eddy current dynamometer was fixed to a strain gauge load cell in order to measure the load applied to the engine. A gas analyzer was also used to measure carbon monoxide (CO), oxygen (O_2), nitrogen oxides (NO_x), unburned hydrocarbons (HC), and nitrogen dioxide (CO_2). Parts per million (ppm) of hexane equivalent and percent volume were used to assess NO_x, HC, and CO, respectively. A glass burette was available at the fuel tank to measure the amount of fuel used per minute. For this reason, a stopwatch was used to measure the diesel and biodiesel fuel separately. The lowest load level applied to the engine was 20%, and the greatest load level was 100%. The length of the dynamometer shaft was used to calculate the torque applied to the engine. All tests on cerium oxide and diesel and ethanol were carried out at a speed that preserved BTDC (before top dead centre). In the experiments, the engine was put through a variety of load conditions. Various compression ratios (CR) were available. The fuel lines were cleaned and the engine was ran for 30 minutes to stabilize at the new state each time the petrol was changed during the experiment. The full engine assembly utilized for the experiment is shown in Figure 1.engine and eddy current dynamometer specifications. The engine exhaust (CO, HC, CO_2, and NO_x) was studied and calculated using a DIGAS SAMPLER attached to an AVL DIG AS gas analyzer at the exhaust.

Figure 1 Experimental Setup with engine and analyzer

3. Result and Discussion

Engine load, ignition pressure, and ignition time were combined to produce six output responses (outputs) from the three input variables. It was decided to use Taguchi's L9 orthogonal array to determine the ideal process condition. 9 tests were therefore carried out in all. The experimental results were normalized in the range of 0 to 1 by employing grey relation approaches. There were six alternatives offered, but it was found that only three of them had higher objective values while the other five had lower values that were preferable. Because of this, during data normalization, the goal values for the parameters BP and BTE were determined using (1), and the remaining values were acquired from (2). Additionally, i(k) for each response's grey relation coefficients were calculated using (3). The grades of 4-year-olds were utilized to determine the relations of the grey. Following consideration of the fairly weighted criteria, the overall grade for grey relations will be established.

Table 2 Experimental results

Exp No.	**Cutting Parameter Level**								
	Engine Load	**Ignition Pressure**	**Ignition timing**	**Brake specific fuel consumption**	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
1	30	200	20	744	0.080	9.55	110	2.48	31.65
2	30	220	22	724	0.070	9.50	102	2.65	32.88
3	30	240	24	718	0.040	9.00	118	2.12	36.30
4	60	200	24	725	0.030	9.25	115	2.42	34.25

5	60	220	20	660	0.124	11.80	220	4.08	32.95
6	60	240	22	620	0.126	11.20	188	2.95	31.15
7	90	200	22	543	0.133	8.40	255	2.80	33.25
8	90	220	24	670	0.120	8.20	275	4.52	37.99
9	90	240	20	488	0.137	12.05	296	6.52	32.54

Table 3 Normalized values

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
1	0.362319	0.24635	0.028269	0.070866	0.073099
0.948718	0.289855	0.237226	0	0.104331	0.252924
0.933333	0.072464	0.145985	0.056537	0	0.752924
0.951282	0	0.191606	0.045936	0.059055	0.453216
0.784615	0.681159	0.656934	0.416961	0.385827	0.263158
0.682051	0.695652	0.547445	0.303887	0.163386	0
0.484615	0.746377	0.036496	0.540636	0.133858	0.307018
0.810256	0.652174	0	0.611307	0.472441	1
0.34359	0.775362	0.702555	0.685512	0.866142	0.203216

Table 4 Deviation sequences of responses

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
0	0.637681	0.75365	0.971731	0.929134	0.926901
0.051282	0.710145	0.762774	1	0.895669	0.747076
0.066667	0.927536	0.854015	0.943463	1	0.247076
0.048718	1	0.808394	0.954064	0.940945	0.546784
0.215385	0.318841	0.343066	0.583039	0.614173	0.736842
0.317949	0.304348	0.452555	0.696113	0.836614	1
0.515385	0.253623	0.963504	0.459364	0.866142	0.692982
0.189744	0.347826	1	0.388693	0.527559	0
0.65641	0.224638	0.297445	0.314488	0.133858	0.796784

Table 5 Grey relational coefficients

Brake specific fuel consumption	**CO**	**HC**	**NOx**	**CO_2**	**BTE**
1	0.43949	0.398836	0.339736	0.349862	0.35041
0.906977	0.413174	0.395954	0.333333	0.358251	0.400938
0.882353	0.350254	0.369272	0.346389	0.333333	0.669276
0.911215	0.333333	0.382148	0.343864	0.346995	0.477654
0.698925	0.610619	0.593074	0.461664	0.448763	0.404255
0.611285	0.621622	0.524904	0.418021	0.37408	0.333333
0.492424	0.663462	0.341646	0.521179	0.365994	0.419118
0.724907	0.589744	0.333333	0.562624	0.48659	1
0.432373	0.69	0.627002	0.613883	0.78882	0.385569

Table 6 Grey relational grades

Exp. No.	**Grey relational grade**	**Rank**
1	0.48	5
2	0.47	7
3	0.49	4
4	0.47	8
5	0.54	3
6	0.48	6
7	0.47	9
8	0.62	1
9	0.59	2

3.1. Analysis of Signal-to-Noise Ratio

Signal-to-noise ratio was designed to analyze the grey relation grade because the conventional approach failed to take into consideration the unpredictable nature of the results. The overall grey relation grade's signal-to-noise ratio was determined using (6) and is shown below.

$$\text{S/N ratio}\,(\eta) = -10\log_{10}\frac{\mu^2}{\sigma^2} \qquad (6)$$

where i stands for the experiment, u for the trial, and Ni for the total number of trials in the experiment.

The output response was examined using JMP Minitab software. Table 6 displays the average of the characteristics selected

The higher-the-better (HB) criterion was used to sort the data because the main goal of the experiment was to find the result with the highest S/N ratio. A high S/N score indicated that the signal had effectively outweighed the random effects of the noise elements:

for each level of the design factors. The S/N ratio for five variables, including Engine load, ignition pressure, and ignition duration, is shown in the primary influence plot (Figure 2) for each one.

The influence of a parameter on response is limited when its line is almost horizontal. The influence of a parameter, on the other hand, increases with the line's inclination. Out of the three parameters, the plot had demonstrated that parameter A (load) had the greatest influence. The ideal process parameter combination that would provide the lowest emissions and the greatest engine performance was determined by the maximum value of the signal-to-noise ratio for each input parameter. Table 6 and Figure 2 showed that the optimal combination of process parameters was A3B2C1.

Table 7 the signal-to-noise ratio

Exp. No.	**Grey relational grade**	**S/N Ratio**
1	0.48	-6.3752
2	0.47	-6.5580
3	0.49	-6.1961
4	0.47	-6.5580
5	0.54	-5.3521
6	0.48	-6.3752
7	0.47	-6.5580
8	0.62	-4.1522
9	0.59	-4.5830

Table 8 Response for the signal-to-noise ratio

GRG			
CONTROL FACTOR	**Engine Load**	**Ignition Pressure**	**Ignition timing**
LEVEL 1	-6.3764	-6.4971	-5.4368
LEVEL 2	-6.0951	-5.3541	-6.4971
LEVEL 3	-5.0977	-5.7181	-5.6354
MAX	-5.0977	-5.3541	-5.4368
MIN	-6.3764	-6.4971	-6.4971
MAX-MIN	1.2787	1.1430	1.0603
RANK	1	2	3

Table 9 ANOVA

GRG						
FACTOR	**DEGREE OF FREEDOM**	**SUM OF SQUARE**	**MEAN SQUARE**	**F - VALUE**	**% CONTRIBUTION**	**RANK**
Engine Load	2	0.0106	0.0053	9.8148	40.48892284	1
Ignition Pressure	2	0.0076	0.0038	7.0370	29.02979374	2
Ignition timing	2	0.0069	0.00345	6.3889	26.35599694	3
ERROR	2	0.00108	0.00054			
TOTAL	8	0.02618				

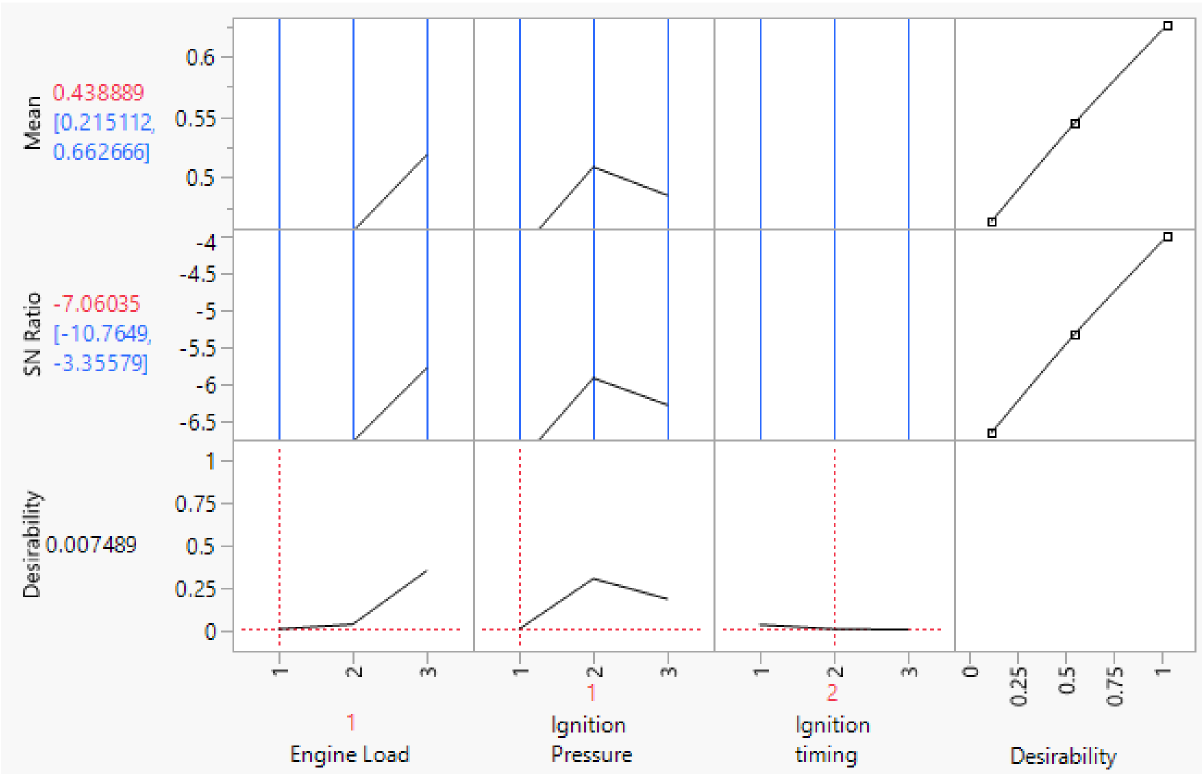

Figure 2 the main effect plots for *S*/*N* ratio

4. Conclusion

- This experimental inquiry looked at the effects of diesel, cerium oxide, and ethanol fuel blends on engine performance and exhaust pollutants. In relation to the prospective use of diesel, cerium oxide, and ethanol blended with conventional diesel as a suitable alternative fuel source, the engine efficiency and emission characteristics had been investigated.

- In the study, three input parameters were modified at once while six separate engine response characteristics were optimized. The experiment was planned using the Taguchi method to create an orthogonal array, which reduced the number of experiments while maintaining the integrity of the data because the investigation plainly indicated that a significant number of test combinations were feasible.
- The non-unidirectional nature of the responses illustrated the difficulty of the optimization problem. The multi-response problem was reduced to a single one when the weighting variables from grey relational analysis were applied, and the best solution was discovered using the test data.

	Initial parameter combination	Optimal parameter combination	
		Prediction	Experimentation
Grey relation grade	A3B2C1	0.62	0.70

- The findings of the experimental investigation were validated using the outcomes of actual experiments. The mixture was shown to be the optimal blend for diesel engines, having little to no effect on the engine's emissions or performance, or on the fuel injection pressure, fuel fraction, or engine load that are related to those factors.

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