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Optimization of Performance and Emission Parameters of Biodiesel with Additives Using Taguchi and Grey Relational Analysis †

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Abstract: The objective of this study is to improve the performance of a diesel engine with direct injection using diethyl ether as an additive and pongamia methyl ester as a fuel and to minimize emissions. The optimization process considers two input factors, the load and the fuel, and evaluates nine response parameters, including brake-specific fuel consumption, brake thermal efficiency, carbon monoxide, oxygen, nitrogen oxides, smoke, and exhaust gas temperature. A series of investigations were carried out to determine the appropriate reaction. Based on the test results, a grey relational analysis was performed to determine the optimal combination of fuel and load. The analysis involved the application of grey relational grade in order to simplify the problem of multiple responses to a single response. The integration of the grey relational grade and the signal-to-noise ratio provides the performance index. The experiment showed that the most effective solution is obtained by using Pongamia methyl ester fuel with a 10% addition of diethyl ether at a load of 30 kg.

Keywords: diesel; pongamia methyl ester; diethyl ether; grey relational analysis

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1. Introduction

Despite the scarcity of resources, petroleum-derived fuels are still readily available. Some areas of the country are extremely active in terms of these few sources. Consequently, countries that do not have these resources face energy and international trade challenges due to their heavy dependence on oil imports [1,2]. The exploration of alternative fuel sources that are readily available in the region, such as biodiesel, vegetable oil, alcohol, and others, is of utmost importance [3,4]. Exhaust, fuel, and engine modifications are the most important methods to optimize performance and reduce emissions due to their environmental and economic benefits [5,6].

The investigation of methyl and ethyl esters from animal and vegetable fats as fuel for diesel engines has been the subject of numerous scientific studies. On the other hand, a few scientists directed their attention toward investigating the impact of vegetable oils and their esters on the performance of engines [7,8]. Other studies were primarily concerned with determining the emission characteristics of the engine [9,10]. A comprehensive analysis of the tests conducted revealed that biodiesel showed favorable results in both engine performance and emissions. Therefore, biodiesel could potentially considered a viable and environmentally sustainable alternative to conventional diesel [11–13]. Reitz et al. [14] have shown that dual-fuel combustion in diesel engines is an effective method of utilizing alternative fuels. Aransiala et al. [15] have evaluated various modern techniques for biodiesel synthesis and proposed a transesterification strategy using animal fats or vegetable oil as a catalyst. Pali et al. [16] investigated the use of sal-methyl ester mixtures in a single-cylinder diesel engine. The objective of their study was to evaluate the influence of various mixtures on emission characteristics, performance, and combustion. The experimental findings indicate that a diesel engine can operate on a fuel combination consisting of sal-methyl ester and diesel with a volume proportion of 40% without the need for modifications. Using Mangifera indicia biodiesel fuel blends, Jadhav et al. [17] enhanced the performance of a compression ignition engine by applying grey relation analysis and the Taguchi technique. Both partial-load and full-load conditions were used to optimize the experiment. In contrast to alternative configurations, the trial results showed that the use of Mangifera indica biodiesel blends led to an improvement under part-load and full-load conditions. To determine the optimum conditions, Yadav et al. [18] applied the Taguchi approach to analyze the gray relation and used the Kano model to determine a correlation between public expectations and performance requirements. Thirteen shape factors were tested, each with three levels, along with five aesthetic qualities. In order to enhance the efficiency of fuel use and reduce the pollutants released from the exhaust, Venkatanarayana et al. [19] adopted the Taguchi approach to investigate the optimal input parameters, including load, fuel blend proportion, compression ratio, injection pressure, and injection timing. The experimental results show that brake-specific fuel consumption is most affected by compression ratio, carbon monoxide (CO) emissions are most affected by load, and smoke opacity is most affected by injection timing. Muqeem et al. [20] improved the control parameters of diesel engines, including injection timing, compression ratio, exhaust gas temperature, Hydro carbon (HC) emissions, and air density, in relation to smoke opacity by applying the Taguchi technique. Determining the optimal values for the performance characteristics requires the use of the signal to noise (S/N) ratio and ANOVA.

The main objective of this study is to optimize the operating parameters of a Direct Injection (DI) diesel engine by using Pongamia biodiesel blends as a replacement fuel. Two important input factors of the engine are the subject of the study: the load and the blend ratio of the fuel. These factors are considered to optimize critical engine responses such as Brake thermal efficiency (BTE), Brake specific fuel consumption (BSFC), Exhaust gas temperture (EGT), hydrocarbon emissions (HC), CO_2, O_2, carbon monoxide (CO), nitrogen oxide emissions (NO_x), and smoke.

2. Materials and Methods

Experimental Setup

On a DI diesel engine with one cylinder, four strokes, and 3.73 kW, the performance and emission characteristics of biodiesel derived from Pongamia methyl ester (PME) combined with diethyl ether (DEE) were assessed. Table 1 displays the parameters of the test engine.

Table 1. Specifications of direct-injection diesel engine.

Engine Model AV1,	kirloskar make
Rated Horse power:	5 hp (3.73 kW)
Rated Speed:	1500 rpm
No of Strokes:	4
Mode of Injection and injection pressure	Direct Injection, 200 kg/cm^2
No of Cylinders:	1
Stroke	110 mm
Bore	80 mm
Compression ratio	16.5

Figure 1 displays the configuration of the experimental setup. The experiments were conducted with an unmodified DI diesel engine. Diesel fuel with additives of 5%, 10%, and 15% was used to operate the engine, along with pure PME and PME-DEE blends. For each fuel type, the experiments were conducted with different loads, ranging from no load to 40 kg. The engine was kept at its intended speed of 1500 rpm during all tests. Performance, exhaust emissions, and smoke density were determined using an exhaust gas analyzer and a smoke meter. A volumetric measurement of fuel consumption was required to determine the brake-specific fuel consumption and brake thermal efficiency.

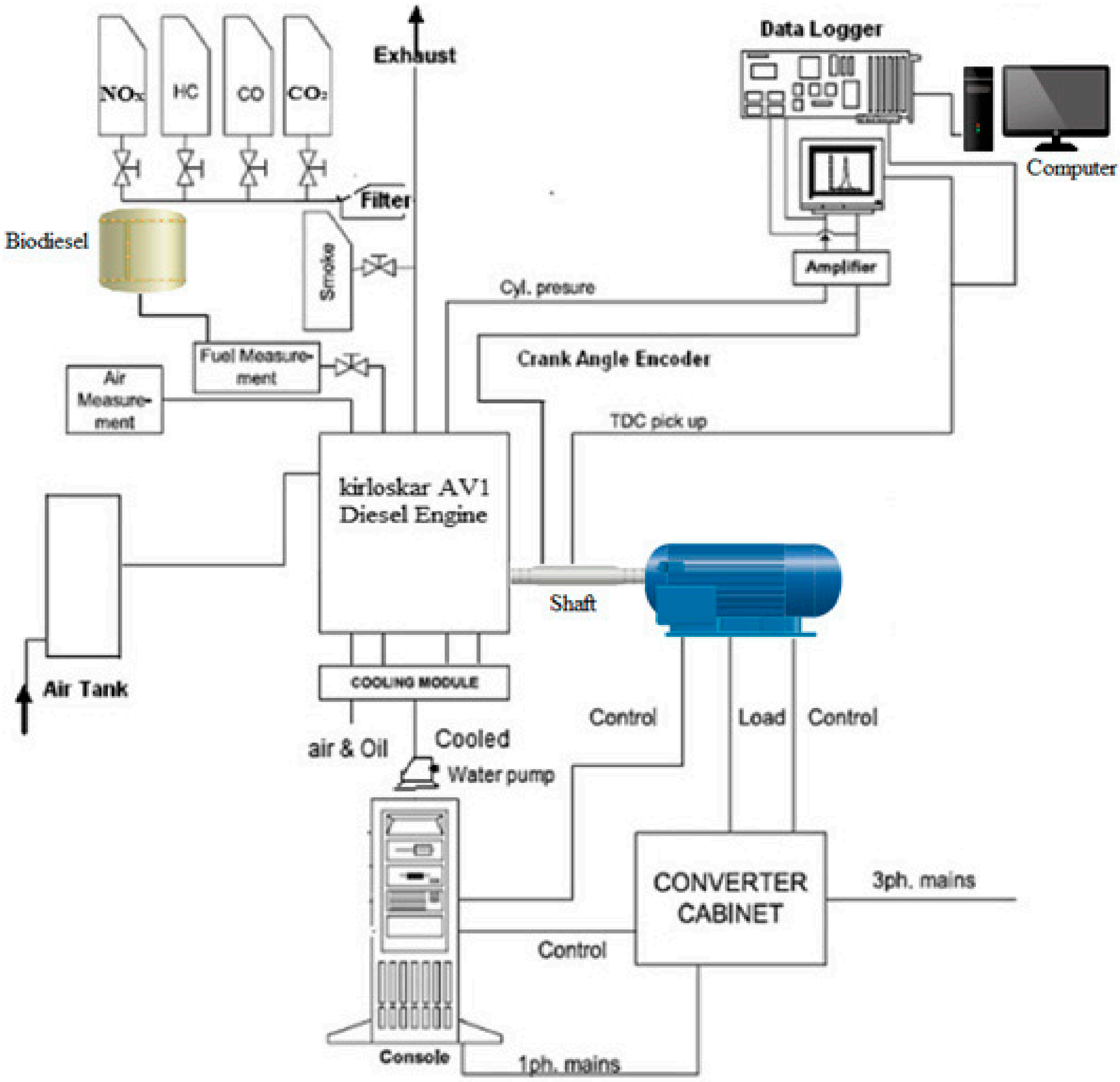

Figure 1. Illustrates the test setup.

Exhaust gas temperatures were also measured under all conditions, and the resulting data can be used to assess engine performance and emission parameters. The performance and emission parameters analyzed in this study include BTE, BSFC, EGT, HC, CO, CO_2, O_2, and NO_X.

3. Methodology

3.1. Taguchi Analysis

This approach uses a rigorous experimental design to minimize process variation. Its main objective is to ensure product quality while minimizing production costs. The orthogonal arrays designed by Taguchi contain extremely large subcomponents. By using these experimental designs, it is possible to approximate significant effects with a limited number of repetitions. The number of degrees of freedom plays a crucial role in the selection of an orthogonal array [21]. We could implement designs that omit all conceivable combinations of the factors to save time and resources. Factorial methods are used in the development of fractional factorial designs, where some of the possible combinations are omitted. These are crucial to the factor screening process as they limit the number of trials to an acceptable level.

$$T = [(M-1) * N] + 1 \quad (1)$$

where (N) Determine the number of factors, the minimum number of trials (T), and the number of levels (M).

Five different conditions are considered in this analysis: Diesel, PME, PME + 5% DEE, PME + 10% DEE, and PME + 15% DEE. Load and fuel are the two components that make up the analysis.

Therefore, the L9 orthogonal array is chosen as it can accommodate at least nine experiments. Orthogonal arrays with two factors represent the simplest conceivable arrangement. Therefore, the square of the number of levels determines the minimal number of tests that must be conducted. The required number of experiments is therefore 25. Therefore orthogonal array L25 was used. By employing an analysis of variance (ANOVA), the influence of specific process variables on response components was investigated.

To mitigate the challenges associated with conducting trials and tests under varying load conditions for different fuel blends, it is imperative to streamline this matter from multiple responses into a solitary response objective. To accomplish this, Grey Relational Analysis (GRA) is implemented. Figure 2 shows the methodology used in grey relational analysis.

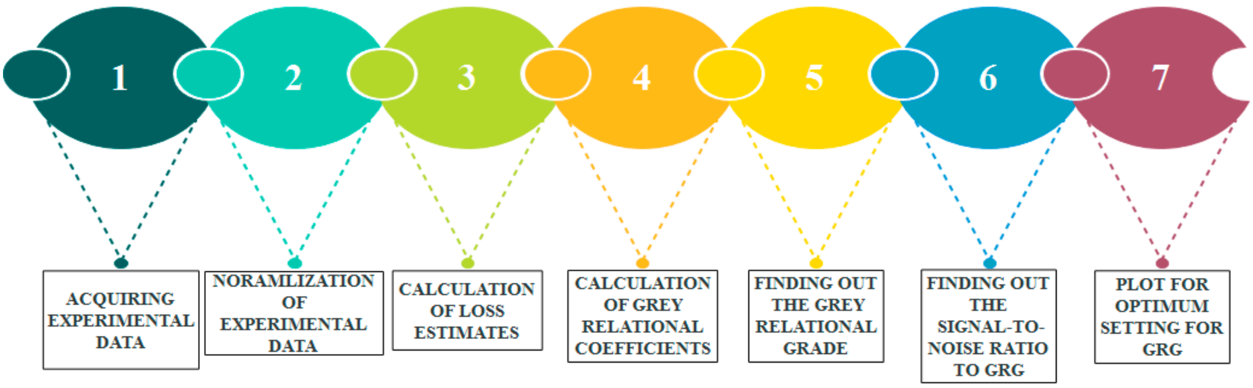

Figure 2. Schematic diagram of gray relational analysis.

The calculation of the grey relation coefficient begins with the investigation of all response parameters, including emission and performance, under various load conditions. This is followed by a weighted conversion of the coefficients into Grey Relational Grade (GRG) values for each load value. The Taguchi analysis system then uses these GRG values as response parameters to generate signal-to-noise (S/N) plots for the given design parameters. S/N plots play a critical role in quantifying the impact that changes in design factor values have on the selected response variables. In creating these charts, a 'lower is better' approach is used to identify responses that need to be reduced, and a 'higher is better' approach is used to identify response variables that need to be improved. Using this approach, it is possible to create S/N diagrams for a variety of selected design features so that we can better understand how these influence the response variables [22,23].

Normalize the original sequence as follows if it contains a "higher-than-better" feature:

$$y_i^* t = \frac{y_i t - min y_i t}{max y_i t - min y_i t} \quad (2)$$

Normalize the original sequence as follows if it contains a "lower-than-better" feature:

$$y_i^* t = \frac{max y_i t - y_i t}{max y_i t - min y_i t} \tag{3}$$

$y_i^* t$ denotes the value reached after generating the grey relations. max $y_i t$ denotes the highest value of $y_i t$ for the t^{th} response, while min $y_i t$ denotes the lowest value of $y_i t$ for the t^{th} response.

3.2. Estimates of Quality Loss

In this estimate of quality loss, the experimental data are scaled from zero to one. $y_o^* t$ represents the deviation sequence of the reference sequence $\Delta_{oi} t$. The equation for $\Delta_{oi} t$ and the comparison sequence $y_i t$ is:

$$\Delta_{oi} t = \left| y_o^* t - y_i^* t \right| \tag{4}$$

where $y_o^* t$ indicates an ideal sequence for the responses. The grey relation level measures the degree of connection between the test series $y_o^* t$ and $y_i^* t$, where i is a number between 1 and n it is indicated by Δ. Table 2 shows the results of the estimation of the quality loss.

Table 2. Results of quality loss estimate.

Experiment No	Fuel Blend	Load (kg)	(egt)Δoi	(bsfc)Δoi	(bth)Δoi	(hc)Δoi	(co)Δoi	(co_2)Δoi	(o_2)Δoi	(no_x)Δoi	(smoke) Δoi
1	D	0	0.054878	0	1	0.051724	0.9	0.084337	0.872727	0.037418	0
2	PME	0	0.04878	0	1	0.12069	1	0.072289	0.036364	0.031805	0.333333
3	PME+5%DEE	0	0.042683	0	1	0.060345	0.6	0.012048	0.872727	0.027128	0.428571
4	PME+10%DEE	0	0.02439	0	1	0.077586	0.4	0	0.6	0.01029	0.142857
5	PME+15%DEE	0	0	0	1	0.258621	0.4	0.012048	0.909091	0	0.238095
6	D	10	0.140244	0.801847	0.483652	0.189655	0.8	0.204819	0.963636	0.12348	0.142857
7	PME	10	0.134146	0.881425	0.433093	0.137931	1	0.156627	0	0.080449	0.380952
8	PME+5%DEE	10	0.146341	0.931664	0.471138	0	0.2	0.180723	0.854545	0.09261	0.52381
9	PME+10%DEE	10	0.140244	0.958158	0.449482	0.25	0.3	0.156627	0.872727	0.079514	0.428571
10	PME+15%DEE	10	0.115854	0.999938	0.504883	0.327586	0.2	0.180723	0.854545	0.064546	0.285714
11	D	20	0.317073	0.559358	0.258898	0.284483	0.6	0.433735	0.054545	0.4116	0.238095
12	PME	20	0.335366	0.609671	0.197414	0.198276	0.9	0.385542	0.090909	0.289055	0.47619
13	PME+5%DEE	20	0.341463	0.617779	0.184161	0.043103	0.2	0.361446	0.890909	0.282507	0.47619
14	PME+10%DEE	20	0.329268	0.621688	0.189036	0.362069	0.2	0.373494	0.6	0.302152	0.285714
15	PME+15%DEE	20	0.341463	0.628514	0.201904	0.456897	0.2	0.39759	0.927273	0.305893	0.142857
16	D	30	0.676829	0.502384	0.135801	0.327586	0.5	0.674699	0.109091	0.719364	0.47619
17	PME	30	0.554878	0.535399	0.076308	0.258621	0.6	0.650602	0.145455	0.669785	0.238095
18	PME+5%DEE	30	0.554878	0.537426	0.080593	0.12931	0.1	0.638554	0.927273	0.697848	0.666667
19	PME+10%DEE	30	0.560976	0.530476	0.076198	0.474138	0.1	0.650602	0	0.724041	0.619048
20	PME+15%DEE	30	0.609756	0.537851	0.066151	0.551724	0.2	0.674699	0.981818	0.633302	0.238095
21	D	40	1	0.431803	0.04628	0.637931	0.9	1	0.018182	0.919551	0.952381
22	PME	40	0.853659	0.491965	0.003497	0.715517	0.8	0.951807	0.054545	0.951356	1
23	PME+5%DEE	40	0.993902	0.52121	0.042473	0.508621	0.2	0.963855	0.927273	1	0.904762
24	PME+10%DEE	40	0.926829	0.508759	0.000185	0.922414	0.2	0.939759	0.072727	0.988775	0.857143
25	PME+15%DEE	40	0.902439	0.529429	0.063518	1	0	0.975904	1	0.967259	0.47619

3.3. Calculation of the Grey Relation Coefficient

Grey relation coefficients quantify the correlation between experimental results that are considered ideal and normalized. The grey relation coefficient $\vartheta_i t$ can be calculated using the following formula:

$$\vartheta_i t = \frac{\Delta_{min} + \vartheta \Delta_{max}}{\Delta_{oi} t + \vartheta \Delta_{max}} \tag{5}$$

Using the loss estimates for the oth and ith experiment, the formula Δ_{oi} calculates the grey relationship coefficient ϑ_i. Δ_{max} denotes the estimated maximum loss, while Δ_{min} stands for the estimated minimum loss. The variable ϑ denoting the discrimination factor is between 0 and 1, with an average value of 0.5.

3.4. Calculation of the Grey Relational Grade

In the conversion of several grey relational grades, the engine performance was assigned a larger share compared to the emission features.

The grey relational grade, is calculated as:

$$\delta_i = \sum_{t=1}^{n} \vartheta_i t \omega_i \tag{6}$$

provides a comprehensive assessment of the extensive range of performance characteristics. The sum of all weighting factors ($\sum \omega_i$) is equal to 1, where ω_i denotes the weighting component.

Table 3 shows the weighted factors associated with nine responses. The weighted average of the grey relationship coefficients corresponding to the selected responses forms the combined grey relational grade. Low, high, and optimal are the three classifications of the signal-to-noise ratio (S/N). Table 4 shows the values of the grey relational coefficient and the total grey relational grade.

Table 3. Responses and their corresponding weighting factors.

Response	Weighting Factors
EGT	0.045
BSFC	0.181
BTHE	0.227
HC	0.045
CO	0.181
CO_2	0.045
O_2	0.181
NO_X	0.045
SMOKE	0.045

Table 4. Calculated grey relational coefficient and overall grey relational grade.

Exp No	Fuel Blend	Load	ξ(egt)	ξ(bsfc)	ξ(bthe)	ξ(hc)	ξ(co)	ξ(co_2)	ξ(o_2)	ξ(no_x)	ξ(smoke)	grg
1	D	0	0.901099	1	0.333333	0.90625	0.357143	0.85567	0.364238	0.930374	1	0.597221
2	PME	0	0.911111	1	0.333333	0.805556	0.333333	0.873684	0.932203	0.940193	0.6	0.675135
3	PME+5%DEE	0	0.921348	1	0.333333	0.892308	0.454545	0.976471	0.364238	0.948536	0.538462	0.60057
4	PME+10%DEE	0	0.953488	1	0.333333	0.865672	0.555556	1	0.454545	0.979835	0.777778	0.648955
5	PME+15%DEE	0	1	1	0.333333	0.659091	0.555556	0.976471	0.354839	1	0.677419	0.618852
6	D	10	0.780952	0.38407	0.50831	0.725	0.384615	0.709402	0.341615	0.80195	0.777778	0.489637
7	PME	10	0.788462	0.361945	0.535852	0.783784	0.333333	0.761468	1	0.861402	0.567568	0.600773
8	PME+5%DEE	10	0.773585	0.349244	0.51486	1	0.714286	0.734513	0.369128	0.843725	0.488372	0.551778
9	PME+10%DEE	10	0.780952	0.342898	0.526603	0.666667	0.625	0.761468	0.364238	0.862793	0.538462	0.525736
10	PME+15%DEE	10	0.811881	0.333347	0.49757	0.604167	0.714286	0.734513	0.369128	0.885667	0.636364	0.537351
11	D	20	0.61194	0.471984	0.65885	0.637363	0.454545	0.535484	0.901639	0.548486	0.677419	0.618737
12	PME	20	0.59854	0.450584	0.716934	0.716049	0.357143	0.564626	0.846154	0.633669	0.512195	0.600901
13	PME+5%DEE	20	0.594203	0.447316	0.730822	0.920635	0.714286	0.58042	0.359477	0.638972	0.512195	0.589962
14	PME+10%DEE	20	0.602941	0.445757	0.725652	0.58	0.714286	0.572414	0.454545	0.623324	0.636364	0.595283
15	PME+15%DEE	20	0.594203	0.443061	0.712348	0.522523	0.714286	0.557047	0.350318	0.620429	0.777778	0.575407
16	D	30	0.42487	0.498811	0.78641	0.604167	0.5	0.425641	0.820896	0.41005	0.512195	0.617407
17	PME	30	0.473988	0.482906	0.867592	0.659091	0.454545	0.434555	0.774648	0.427429	0.677419	0.629707
18	PME+5%DEE	30	0.473988	0.481962	0.861188	0.794521	0.833333	0.439153	0.350318	0.417415	0.428571	0.614406
19	PME+10%DEE	30	0.471264	0.485213	0.867758	0.513274	0.833333	0.434555	1	0.408483	0.446809	0.721923
20	PME+15%DEE	30	0.450549	0.481765	0.883156	0.47541	0.714286	0.425641	0.337423	0.441189	0.677419	0.591586
21	D	40	0.333333	0.536594	0.915282	0.439394	0.357143	0.333333	0.964912	0.352224	0.344262	0.62769
22	PME	40	0.369369	0.50405	0.993055	0.411348	0.384615	0.344398	0.901639	0.344505	0.333333	0.632954
23	PME+5%DEE	40	0.334694	0.489615	0.921704	0.495726	0.714286	0.341564	0.350318	0.333333	0.355932	0.576469
24	PME+10%DEE	40	0.350427	0.495658	0.999629	0.351515	0.714286	0.34728	0.873016	0.335847	0.368421	0.685406
25	PME+15%DEE	40	0.356522	0.485706	0.887283	0.333333	1	0.338776	0.333333	0.340771	0.512195	0.617717

The signal-to-noise ratio (S/N ratio) quantifies the proportion of extraneous disturbance to desired output. It incorporates both the mean and variability of the signal. An alternative conceptualization involves dividing the energy consumed for the intended purpose by the energy lost [24,25]. There are three possible scenarios: "Nominal-the-better" (NTB) for determining the optimal characteristic, which is the median of the specified upper and lower standard limits as described in Equations (7)–(9); "Larger the better" (LTB) for maximizing problems; and "Smaller the better" (STB) for minimizing problems.

For larger the better:

$$\frac{S}{N} = -10\left[\log\left(\sum\left(\frac{1}{x^2}\right)/n\right)\right] \tag{7}$$

For smaller the better:

$$\frac{S}{N} = -10\left[\log\left(\sum\left(x^2\right)/n\right)\right] \tag{8}$$

For nominal the better:

$$\frac{S}{N} = -10\left[\log\left(\sum\left(s^2\right)\right)\right] \tag{9}$$

Responses for the given factor level combination are denoted by 'x'. For the combination of factor levels, 'n' denotes the number of responses. 's' means the standard deviation of the responses for each noise component of a specific combination of factor levels.

The criteria "larger is better" is applicable to brake thermal efficiency (BTE), as our aim is to optimize it. In contrast, for carbon dioxide (CO_2), hydrocarbons (HC), NOx (nitrogen oxides), CO, and BSFC, the criteria "smaller the better" is optimal, as our aim is to reduce these pollutants. Table 5 shows the exact values measured using the Minitab19 software in this study. The relevant data can be found in Tables 6 and 7.

Table 5. Response of signal-to-noise ratio.

Level	Fuel Blend	Load
1	−4.617	−4.048
2	−4.050	−5.354
3	−3.991	−4.497
4	−4.621	−3.965
5	−4.638	−4.053
Delta	0.647	1.389
Rank	2	1

Table 6. Enhanced results using GRG.

S. no.	Factors	Optimal Level	Optimal Value
1	Load	4	30 kg
2	Type of fuel blend	2	PME + 10% DEE

Table 7. Experimental results.

EXP	Load (kg)	Fuel Blend	EGT (^{0}C)	BSFC (kw-hr)	BTE (%)	HC (ppm)	CO (%)	CO_2 (%)	O_2 (%)	NO_X (ppm)	Smoke (HSU)
1	30	PME + 10% DEE	193	0.3664	26.4177	76	0.05	7.2	20.38	826	49

4. Results and Discussion

The two input parameters (fuel and load) and the nine output parameters (EGT, BSFC, BTE, HC, CO, CO_2, O_2, NO_x, and smoke) are involved in the generation of numerous permutations. EGT, BSFC, BTE, HC, CO, CO_2, O_2, NO_x, and smoke are all components of the orthogonal array. The normalized data were then used to create tables, and the grey relation coefficient was calculated. The grey value is then determined by using weighting parameters.

Assign the signal-to-noise ratio (S/N ratio) for each plane after calculating the S/N ratio for the entire grey relation grade. The MINITAB software is used to perform this analysis. Table 4 illustrates the expected grey relation coefficient and the total grey relation grade, while Table 5 shows the response of the S/N ratio for fuel and load. Figure 3 shows the main effects of the signal-to-noise ratio. At a weight of 30 kg, the ideal load is four. As shown in Table 6, the optimal fuel is three, and the consistent fuel type is PME + 10% DEE. The expected results were in excellent contrast with the empirical data. From the data in Table 5, it can be seen that the load difference has a greater influence on the responses than the fuel. It could be discussed that the operating load allows for more convenient manipulation of the responses in contrast to the influence of fuel. Based on the results of the S/N ratio analysis, the fuel and load show the most favorable responses at levels three and four, respectively, with S/N ratios of –3.991 and –3.965. The use of PME + 10% DEE at a load of 30 kg optimizes the performance of the engine, as shown in Figure 3.

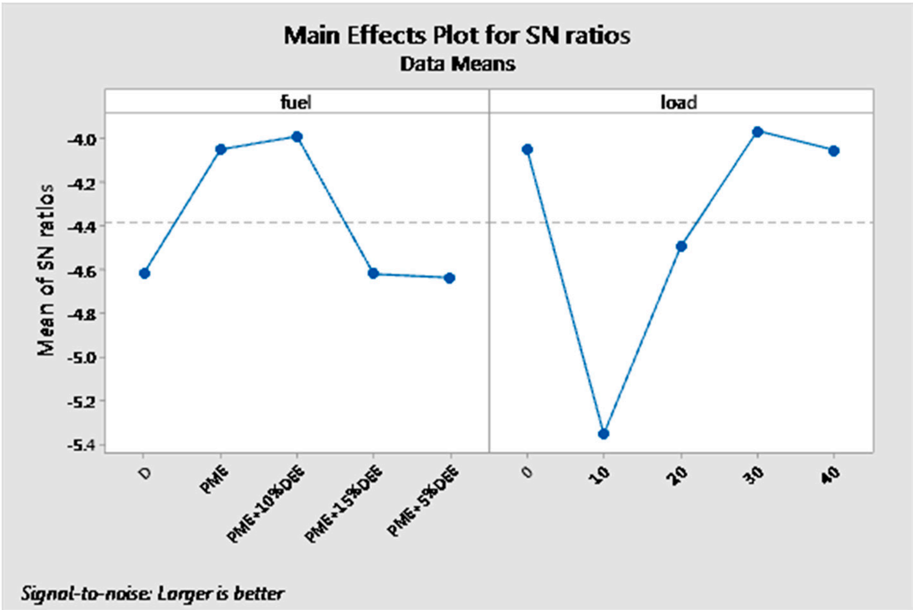

Figure 3. Main effect plots for signal-to-noise ratio for fuel blend and load.

Author Contributions: R.V.L.: writing—original draft, review & editing; G.D.T.: conceptualization, resources; R.K.M.: formal analysis, visualization; J.S.: data curation, investigation, methodology. All authors have read and agreed to the published version of the manuscript.

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