International Journal of Engineering Research and Science & Technology

IJERST

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 2(1) (2025)

ijerst.editor@gmail.com

editor@ijerst.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 2(1), 2025

OPTIMIZATION OF DIESEL ENGINE PARAMETERS TO IMPROVE PERFORMANCE FOR SAL SEED BIO-DIESEL BLEND

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Abstract: The increasing demand for sustainable and eco-friendly energy sources has led to the exploration of biodiesel as an alternative to conventional diesel. Sal seed biodiesel, derived from *Shorea robusta*, offers a promising solution, but its use in diesel engines requires optimization of engine parameters to enhance performance and minimize harmful emissions. This study explores the optimization of diesel engine parameters for Sal seed biodiesel blends to reduce emissions and enhance engine performance. A Taguchi L16 orthogonal array design was employed to systematically evaluate the effects of three key input parameters: engine load (ranging from 0.2 kg to 13.5 kg), biodiesel blend percentage (B0, B10, B20, B30, B50), and injection pressure (190, 200, 210, and 220 bar). The use of the Taguchi method reduced the number of required experiments from potentially dozens to just 16 trials, efficiently capturing the interactions between these parameters. The optimal combination for maximizing engine performance was found at 200 bar injection pressure and a B30 blend. This research provides valuable insights into the effective use of Sal seed biodiesel in diesel engines, contributing to cleaner and more sustainable engine operations.

Key words: Sal seed Biodiesel, Diesel engine, Taguchi optimization , ANOVA, Pressure, Load

Received: 15-5-2025 Accepted: 6-7-2025 Published: 17-7-2025

Introduction

As global concerns over environmental degradation and the unsustainable use of fossil fuels grow, there has been a strong push towards the development and adoption of renewable energy sources. Among these, biodiesel has gained attention as an alternative to traditional diesel due to its environmental benefits, such as reduced emissions of greenhouse gases, lower toxicity, and biodegradability. Biodiesel, produced from vegetable oils and animal fats, offers a promising solution to mitigate the negative impact of conventional diesel fuels. One such biodiesel source is Sal seed oil, derived from the seeds of *Shorea robusta*, a tree commonly found in tropical regions of South Asia. Sal seed oil has garnered significant interest due to its abundance, high oil yield, and suitability for use in biodiesel production. However, the use of Sal seed biodiesel in conventional diesel engines presents several challenges, primarily due to differences in fuel properties like viscosity, density, and energy content compared to conventional diesel. The performance and emission characteristics of engines fueled with Sal seed biodiesel blends are influenced by several key diesel engine parameters, such as injection timing, compression ratio, injection pressure, and engine speed. These parameters, when optimized, can enhance engine performance, fuel efficiency, and reduce the harmful emissions typically associated with diesel combustion, including nitrogen oxides (NO_x), carbon monoxide (CO), unburned hydrocarbons (HC), and particulate matter. Optimizing these engine parameters for Sal seed biodiesel blends is critical to harnessing their full potential as a clean and efficient fuel alternative. This optimization process requires understanding the complex interactions between fuel properties and engine operating conditions, ensuring that the engine operates at peak efficiency while minimizing emissions. Additionally, the adoption of Sal seed biodiesel could contribute to local economies by providing an alternative energy source that reduces dependence on imported petroleum.

2.Literature Review

Biodiesel has been recognized as a promising renewable alternative to fossil fuels due to its potential to reduce harmful emissions and reliance on non-renewable resources. Sal seed biodiesel, derived from *Shorea robusta*, is particularly of interest in regions where the tree is abundant. However, using Sal seed biodiesel blends in diesel engines presents unique challenges related to fuel properties, including high viscosity and poor low-temperature flow properties compared to conventional diesel. 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**,**12**,**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.

3. Methology

The experimental study employed a Taguchi L16 orthogonal array to systematically evaluate and optimize the performance and emission characteristics of a single-cylinder, four-stroke diesel engine operating on Sal seed biodiesel blends. The three main input parameters considered were:

- Engine load: Varied from 0.2 kg to 13.5 kg
- Blend percentage: B0 (pure diesel), B10, B20, B30, B50
- Injection pressure: 190, 200, 210, and 220 bar

This design approach reduced the number of required experiments from potentially dozens to just 16 strategically planned trials, while still capturing the interactions between key parameters.

The results indicated that B30 blend, when operated at 200 bar injection pressure and medium to high loads, consistently delivered higher brake thermal efficiency (BTE) and lower brake specific fuel consumption (BSFC). Additionally, this combination showed significant reductions in CO, HC, and smoke emissions, owing to better combustion quality enhanced by the presence of ZnO nanoparticles. The Taguchi method allowed identification of the most influential parameters on engine performance and emissions. The analysis confirmed that blend ratio and injection pressure were the most significant factors, while engine load had a strong secondary influence. These findings demonstrate that optimized biodiesel blends can deliver improved efficiency and lower emissions, making Sal seed biodiesel a promising alternative fuel for CI engines.

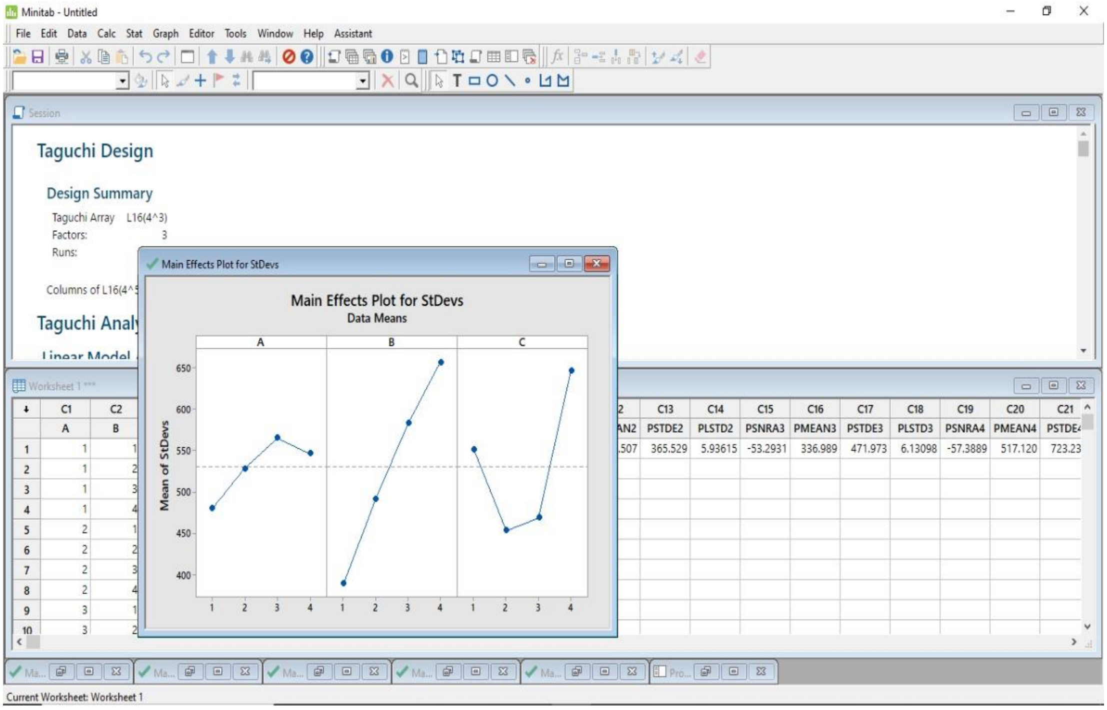

Figure:1 Taguchi optimization using mini tab

4. Results and discussions

The results validate that B30 SAL seed bio-diesel blend offers the most favorable balance between engine performance, fuel economy, and emissions. The blend is suitable for long-term engine operation with minimal modifications, supporting its potential for practical application in sustainable fuel strategies.

Table:1 Performance based Taguchi L16 Orthogonal array

S.NO	A	B	C	Pressure	Load	Blend %	BTE	BSFC	BP
1	1	1	1	190	0.2	0.2	12	0.701	2.03
2	1	2	2	190	4.5	B10	20	0.421	3.49
3	1	3	3	190	9	B30	33	0.258	3.04
4	1	4	4	190	13.5	B50	30	0.290	5.91
5	2	1	2	200	0.2	B10	16	0.526	2.19
6	2	2	1	200	4.5	0.2	25	0.334	3.70
7	2	3	4	200	9	B50	33	0.259	4.98
8	2	4	3	200	13.5	B30	47	0.184	5.89
9	3	1	3	210	0.2	B30	23	0.373	2.26
10	3	2	4	210	4.5	B50	36	0.237	3.95
11	3	3	1	210	9	0.2	37	0.231	4.96
12	3	4	2	210	13.5	B10	41	0.206	5.93
13	4	1	4	220	0.2	B50	39	0.219	3.71

14	4	2	3	220	4.5	B30	46	0.188	5.89
15	4	3	2	220	9	B10	48	0.172	5.99
16	4	4	1	220	13.5	B0	49	0.156	6.91

Table:2 Taguchi Analysis: BTE, BP versus A, B, C

Term	Coef	SE Coef	T	P
Constant	15.2484	0.2849	53.521	0.000
A 1	-1.8279	0.4935	-3.704	0.010
A 2	-0.4432	0.4935	-0.898	0.404
A 3	-0.2071	0.4935	-0.420	0.689
B 1	-4.4520	0.4935	-9.022	0.000
B 2	0.0638	0.4935	0.129	0.901
B 3	0.9572	0.4935	1.940	0.100
C 1	-0.2797	0.4935	-0.567	0.591
C 2	-0.1613	0.4935	-0.327	0.755
C 3	-0.4062	0.4935	-0.823	0.442

In this table, we can see the results of a Taguchi study that looked at the relationship between the response variables (BTE, BP) and three independent variables (A, B, and C). The Coef column shows the predicted coefficients for all terms, whereas the SE Coef column shows the standard error of the coefficients. T is the coefficient's ratio to its standard error, and P is the factor's statistical significance. Among the components in the response variable, the terms A 1 and B 1 stand out as significantly significant (P-value less than 0.05). In contrast, terms A2, A3, B2, and C, which have large P-values, do not significantly impact the response.

Table: 3Analysis of Variance for SN ratios/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	38.890	38.890	12.963	9.98	0.010	1.1396	95.69%	89.22%
B	3	130.048	130.048	43.349	33.38	0.000			
C	3	3.949	3.949	1.316	1.01	0.450			
Residual Error	6	7.793	7.793	1.299					
Total	15	180.679							

This table presents the Analysis of Variance (ANOVA) for the Signal-to-Noise (SN) ratios and the corresponding model summary. It shows the contribution of each factor (A, B, C) and the residual error to the overall variation in the data. The "Seq SS" and "Adj SS" columns indicate the sum of squares for each factor, both in the sequence and after adjustments. The "Adj MS" column gives the adjusted mean squares, and the "F" value helps assess the significance of each factor. The "P" value for factor A (0.010) and factor B (0.000) indicates they are statistically significant, while factor C (0.450) is not. The model has an R-Sq value of 95.69%, suggesting it explains most of the variation in the data. The adjusted R-Sq (89.22%) further supports the model's effectiveness, accounting for the factors in the analysis.

Table:4 Linear Model Analysis: Means versus A, B, C Estimated Model Coefficients for Means

Term	Coef	SE Coef	T	P
Constant	18.9322	0.4698	40.299	0.000
A 1	-5.2484	0.8137	-6.450	0.001
A 2	-1.7122	0.8137	-2.104	0.080
A 3	0.3303	0.8137	0.406	0.699
B 1	-6.4084	0.8137	-7.876	0.000
B 2	-0.9284	0.8137	-1.141	0.297
B 3	2.3141	0.8137	2.844	0.029
C 1	-1.3572	0.8137	-1.668	0.146
C 2	-1.1072	0.8137	-1.361	0.223
C 3	1.8278	0.8137	2.246	0.066

This table shows the estimated model coefficient of means on the A, B, and C factors based on the linear model analysis. The Coef column contains the estimated coefficients for each term, whereas the SE Coef column contains the standard error of each coefficient. The T-value is the coefficient's ratio to its standard error, and the P-value is an indication of the factor's statistical significance. Factors A 1 and B 1 are highly significant in influencing the response variable, as evidenced by their low P-values (0.000 and 0.001, respectively). The third component, B3, is similarly statistically significant (P=0.029). However, other terms A 2, A 3, B 2, C 1, C 2, and C 3 do not significantly impact the outcome because their P-values are larger.

Table:5 Analysis of Variance for Means/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	298.19	298.19	99.397	28.15	0.001	1.8792	96.67%	91.68%
B	3	290.05	290.05	96.685	27.38	0.001			
C	3	27.26	27.26	9.085	2.57	0.150			
Residual Error	6	21.19	21.19	3.531					
Total	15	636.69							

A summary of the model and the results of the analysis of variance (ANOVA) on the means are presented in the table below. It breaks down the response variable's variance into its component parts, which are the sources of the error (A, B, and C) and the residual error. Two columns, "Seq SS" and "Adj SS," show the total number of sums of squares of a specific element both before and after adjustment. The adjusted mean squares (Adj MS) and F-values (used to find the importance of each factor) are displayed in the corresponding columns. A and B are statistically significant in explaining the data fluctuation, while C is not, since their respective P-values are 0.001 and 0.150, respectively. The model explains 96.67% of the observed variation in the data, as shown by the R-Sq and an adjusted R-Sq of 91.68% after adjusting for degrees of freedom.

Table:6 Response for Signal to Noise Ratios / Larger is better

Level	A	B	C
1	13.42	10.80	14.97
2	14.81	15.31	15.09
3	15.04	16.21	14.84
4	17.73	18.68	16.10
Delta	4.31	7.88	1.25
Rank	2	1	3

Table:7 Response for Means

Level	A	B	C
1	13.68	12.52	17.57
2	17.22	18.00	17.83
3	19.26	21.25	20.76
4	25.56	23.95	19.57
Delta	11.88	11.43	3.18
Rank	1	2	3

Figure:2 Main effects plot for means

The major effect plot of the means of factors A, B, and C is represented by this number. In every graphic, the data points represent the means of the various factor levels. The data clearly shows an increasing trend for factor A, suggesting that high levels of A result in high means. There is an increasing trend in both factor A and component B, but factor B is more likely to affect the response variable because its slope is mean steeper. In contrast, factor C shows very little variation among levels and a relatively flat trend overall, meaning it has little to no impact on the response. It is clear from the overarching trends that factors A and B have a more significant impact on the means than factor C.

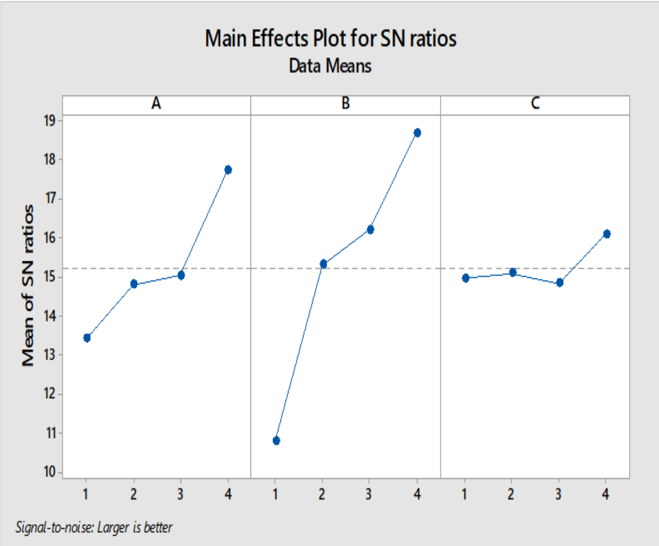

Figure:3 Main effects plot for SN ratios

This figure's main effects plot aims to maximize Signal-to-Noise (SN) ratios, with bigger values being preferred. An apparent upward trend in factor A indicates that increasing A levels will raise SN ratios, which is a desirable outcome. Factor b likewise shows a positive trend, with rising SN ratios resulting from higher levels of B. Contrarily, factor C's effect on the SN ratio has changed very little, suggesting that it has only a minor impact on the response. The SN ratio enhancement appears to be significantly influenced by components A and B, with factor C playing a very minor contribution.

Table:8 Taguchi Analysis: BSFC, BP versus A, B, C

Term	Coef	SE Coef	T	P
Constant	-1.3984	0.1977	-7.075	0.000
A 1	1.0613	0.3423	3.100	0.021
A 2	0.2068	0.3423	0.604	0.568
A 3	-0.2743	0.3423	-0.801	0.454
B 1	1.9960	0.3423	5.830	0.001
B 2	-0.2928	0.3423	-0.855	0.425
B 3	-0.6892	0.3423	-2.013	0.091
C 1	0.6456	0.3423	1.886	0.108
C 2	0.2541	0.3423	0.742	0.486
C 3	-0.2447	0.3423	-0.715	0.502

The results of a Taguchi analysis showing how factors A, B, and C affect BSFC and BP are displayed. Coef represents the estimated coefficients of all terms, and SE Coef stands for their standard errors. These are displayed under the column titles. The number of standard errors between the coefficient and zero is shown by the values of T, and the statistical significance is determined by the value of P. With P-values of 0.021 and 0.000, respectively, for Measurement A 1 and B 1, we can deduce that these two variables significantly impact the response variable. In contrast, C1, C2, and C3 did not have a substantial effect on BSFC and BP because their P-values were determined to be more significant than those of A2, A3, B2, and B3.

Table: Analysis of Variance for SN ratios/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	8.928	8.928	2.9759	4.76	0.050	0.7906	90.35%	75.87%
B	3	22.291	22.291	7.4305	11.89	0.006			
C	3	3.881	3.881	1.2938	2.07	0.206			
Residual Error	6	3.750	3.750	0.6251					
Total	15	38.851							

The table that is included summarizes the model and displays the results of an Analysis of Variance (ANOVA) on the Signal-to-Noise (SN) ratios. It breaks down the residual error and the fluctuation in the SN ratios into its component parts, which are sources A, B, and C. The columns labeled Seq SS and Adj SS offer the sum of squares of each source before and after adjustment, respectively. The Adj MS column contains the adjusted mean squares. Every component's relevance can be ascertained with the use of the "F" value. Because of its large-scale effect on the SN ratio, factor B has a significant P-value of 0.006, while factor A is nearly significant with a P-value of 0.050. A greater P-value (0.206) for Factor C indicates that it has no significant impact. R-Sq adjusted (75.87 percent) shows that the model is fairly robust, and R-Sq value of 90.35 percent shows that the model catches most of the fluctuations in SN ratios. Additionally, the model captures the components in the analysis.

Table:9 Linear Model Analysis: Means versus A, B, C Estimated Model Coefficients for Means

Term	Coef	SE Coef	T	P
Constant	2.36203	0.07374	32.034	0.000
A 1	-0.34453	0.12771	-2.698	0.036
A 2	-0.10416	0.12771	-0.816	0.446
A 3	-0.09366	0.12771	-0.733	0.491
B 1	-0.86091	0.12771	-6.741	0.001
B 2	-0.08578	0.12771	-0.672	0.527
B 3	0.12422	0.12771	0.973	0.368
C 1	0.01572	0.12771	0.123	0.906
C 2	0.00359	0.12771	0.028	0.978
C 3	-0.10166	0.12771	-0.796	0.456

The predicted coefficients, standard error, t-value, and p-value are all part of this table that shows the outcomes of a linear model analysis of the means difference of variables A, B, and C. A value of 2.36203 is assigned to the coefficients, which are utilised to provide the impact and impacts of individual terms on the dependent variable. Key terms, such as A1, with a p-value of 0.036 and a coefficient value of -0.34453, show a substantial impact. However, terms A2, A3, B2, C1, C2, and C3 have larger p-values, suggesting that their effects are not statistically different at the 0.05 level.

Table:10 Analysis of Variance for Means/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	1.72983	1.72983	0.57661	6.63	0.025	0.2949	93.54%	83.86%
B	3	5.76161	5.76161	1.92054	22.08	0.001			
C	3	0.06950	0.06950	0.02317	0.27	0.848			
Residual Error	6	0.52195	0.52195	0.08699					
Total	15	8.08290							

Table:11 Response for Signal to Noise Ratios

Level	A	B	C
1	-0.3371	0.5976	-0.7527
2	-1.1915	-1.6912	-1.1443
3	-1.6727	-2.0876	-1.6431
4	-2.3922	-2.4123	-2.0534
Delta	2.0551	3.0099	1.3007
Rank	2	1	3

Table:12 Response for Means

Level	A	B	C
1	2.018	1.501	2.378
2	2.258	2.276	2.366
3	2.268	2.486	2.260
4	2.904	3.184	2.444
Delta	0.887	1.683	0.184
Rank	2	1	3

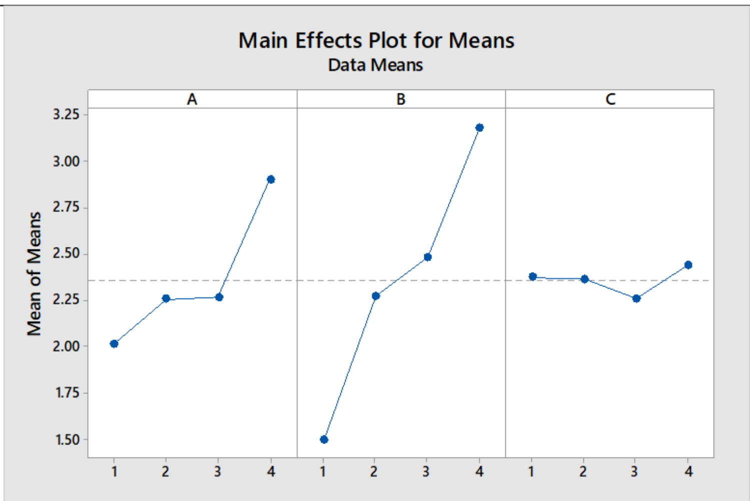

Figure:4 Main effects plot for means

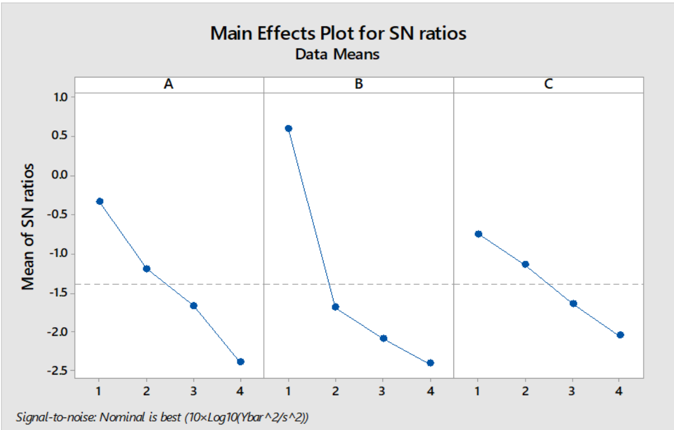

Figure:5 Main effects plot for SN ratios

The representation of the main effects plot of signal-to-noise (SN) ratios is shown in this figure. It displays the means of the variables A, B, and C. Whereas the y-axis shows the average SN ratio, the x-axis shows the different proportions of each variable, which can be anywhere from 1 to 4. A negative trend is evident in all three variables, with lower averages of SN ratios observed for increasing values. In order to see how each variable affects the system's performance, the current suggests that reducing SN ratios would go hand-in-hand with increasing each of the parameters.

Table:13 Taguchi Analysis: BSFC, BTE versus A, B, C

Term	Coef	SE Coef	T	P
Constant	-2.78710	0.03664	-76.075	0.000
A 1	0.19816	0.06346	3.123	0.021
A 2	0.02874	0.06346	0.453	0.667
A 3	-0.07523	0.06346	-1.186	0.281
B 1	0.26844	0.06346	4.230	0.005
B 2	-0.02740	0.06346	-0.432	0.681

B 3	-0.11248	0.06346	-1.773	0.127
C 1	0.12976	0.06346	2.045	0.087
C 2	0.04844	0.06346	0.763	0.474
C 3	-0.08405	0.06346	-1.325	0.234

The results of a Taguchi test that looked at the correlation between Brake Thermal Efficiency (BTE) and Brake Specific Fuel Consumption (BSFC) among A, B, and C variables are shown in the table below. Coefficients (Coef) with an estimated value of -2.78710 for the constant term correspond to the remaining terms. A1 has produced a substantial effect on the response variable, as shown by its coefficient of 0.19816 and p-value of 0.021, which is an intriguing observation itself. A2, A3, B2, B3, C2, and C3 are only a few examples of words whose lower p-values suggest that their impacts are not statistically significant.

Table:14 Analysis of Variance for SN ratios/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	0.2750	0.2750	0.09168	4.27	0.062	0.1465	86.47%	66.17%
B	3	0.4080	0.4080	0.13599	6.33	0.027			
C	3	0.1405	0.1405	0.04682	2.18	0.191			
Residual Error	6	0.1289	0.1289	0.02148					
Total	15	0.9523							

This table presents the Analysis of Variance (ANOVA) for the Signal-to-Noise (SN) ratios, summarizing the model's statistical performance. The factors A, B, and C are analysed, with A showing a significant effect (p = 0.062) on the response variable, while B (p = 0.027) is statistically significant, and C (p = 0.191) is not. The R-squared value of 86.47% indicates that the model explains most of the variation in SN ratios, with an adjusted R-squared of 66.17%, accounting for the number of predictors in the model. The residual error represents the remaining unexplained variation, with a sum of squares of 0.1289.

Table:15 Linear Model Analysis: Means versus A, B, C

Term	Coef	SE Coef	T	P
Constant	16.8673	0.4763	35.410	0.000
A 1	-4.7836	0.8251	-5.798	0.001
A 2	-1.5795	0.8251	-1.914	0.104
A 3	0.3885	0.8251	0.471	0.654
B 1	-5.3900	0.8251	-6.533	0.001
B 2	-0.8448	0.8251	-1.024	0.345

B 3	2.1227	0.8251	2.573	0.042
C 1	-1.3146	0.8251	-1.593	0.162
C 2	-1.0767	0.8251	-1.305	0.240
C 3	1.8830	0.8251	2.282	0.063

Table:16 Analysis of Variance for Means/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	244.89	244.89	81.631	22.48	0.001	1.9054	95.63%	89.07%
B	3	204.72	204.72	68.241	18.80	0.002			
C	3	26.77	26.77	8.922	2.46	0.161			
Residual Error	6	21.78	21.78	3.631					
Total	15	498.17							

The summary of the statistical model, the table below shows the results of the means' Analysis of Variance (ANOVA). The factors A, B, and C form the basis of their analysis. Both Factor A and Factor B are statistically significant, with p-values of 0.001 and 0.002, respectively. Meanwhile, factor C does not show any significant results ($p = 0.161$). An R-squared value of 95.63 and an adjusted R-squared value of 89.07, both of which reflect the number of predictors, are displayed by the model. A sum of squares of 21.78 represents the unexplained variation, also known as the residual error. Due to their large F-values, factors A and B exert a substantial impact on the response variable.

Table: 17 Response for Signal to Noise Ratios

Level	A	B	C
1	-2.589	-2.519	-2.657
2	-2.758	-2.815	-2.739
3	-2.862	-2.900	-2.871
4	-2.939	-2.916	-2.881
Delta	0.350	0.397	0.224
Rank	2	1	3

Table:18 Response for Means

Level	A	B	C

1	12.08	11.48	15.55
2	15.29	16.02	15.79
3	17.26	18.99	18.75
4	22.84	20.98	17.38
Delta	10.76	9.50	3.20
Rank	1	2	3

Figure:6 Main effects plot for SN ratios

The means of the response variable are displayed against the components A, B, and C in these main effects plot. For each element, the plots would show the average response at different levels (from 1 to 4). There is a clear positive trend in Factor A; the mean reaction grows in proportion to the factor's level. Similar to how factor A appears to have a sharp upward trend, factor B appears to have a more gradual one. Meanwhile, factor C displays a rather complex pattern with some fluctuations, suggesting that the factor's impact on the response is less direct than that of the other two factors. The correlation between the variables and the average replies can be better.

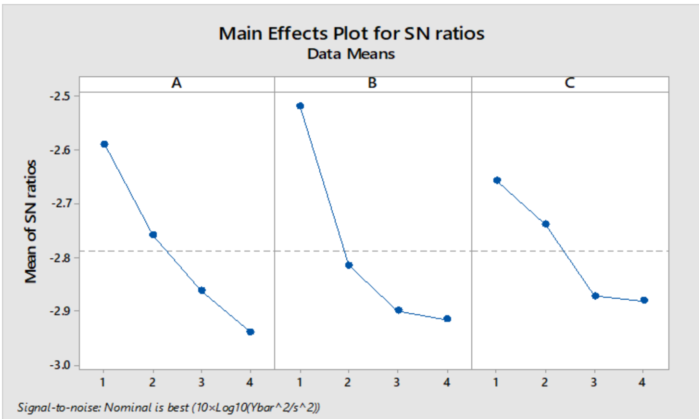

Figure:7 Main effects plot for SN ratios

This figure presents the main effects plot for Signal-to-Noise (SN) ratios, showing the mean SN ratios at different levels (1 to 4) for factors A, B, and C. For factor A, there is a clear decreasing trend, with SN ratios becoming more negative as the levels increase. Similarly, factor B also shows a downward trend, although the change is less pronounced compared to factor A. Factor C shows a slight decrease at first but then levels off, indicating a more subtle effect. Overall, this plot highlights how each factor influences the

SN ratio, with higher levels generally associated with lower SN ratios, which could be indicative of the desired outcomes in certain experimental setups.

Table:19 Taguchi Analysis: BSFC, BTE versus A, B, C

Term	Coef	SE Coef	T	P
Constant	23.4337	0.6795	34.484	0.000
A 1	-6.9352	1.1770	-5.892	0.001
A 2	-2.2741	1.1770	-1.932	0.102
A 3	0.5996	1.1770	0.509	0.629
B 1	-7.8454	1.1770	-6.666	0.001
B 2	-1.1917	1.1770	-1.012	0.350
B 3	3.0969	1.1770	2.631	0.039
C 1	-1.9416	1.1770	-1.650	0.150
C 2	-1.5709	1.1770	-1.335	0.230
C 3	2.7287	1.1770	2.318	0.060

This table presents the results of a Taguchi analysis for Brake-Specific Fuel Consumption (BSFC) and Brake Thermal Efficiency (BTE) across factors A, B, and C. The constant term is 23.4337, representing the baseline value. Factor A1 shows a significant negative impact on BSFC and BTE with a coefficient of -6.9352 and a p-value of 0.001. A2 also has a negative effect, but its p-value of 0.102 indicates it is not statistically significant. A3 has a small positive coefficient and is not significant (p = 0.629). For factor B, B1 has a significant negative effect (p = 0.001), while B2 is not significant (p = 0.350). B3 shows a positive effect with a p-value of 0.039, indicating a significant contribution. Factor C's terms (C1, C2, C3) show mixed results, with C3 being close to significance (p = 0.060).

Table: 20 Analysis of Variance for St Devs/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	511.02	511.02	170.339	23.05	0.001	2.7182	95.75%	89.38%
B	3	431.39	431.39	143.796	19.46	0.002			
C	3	57.19	57.19	19.063	2.58	0.149			
Residual Error	6	44.33	44.33	7.388					
Total	15	1043.93							

This table presents the results of the Analysis of Variance (ANOVA) for the standard deviations (St Devs), summarizing the model's performance. Factor A and factor B show significant effects on the response variable, with p-values of 0.001 and 0.002, respectively, indicating strong contributions to the variation in St Devs. Factor C, however, has a higher p-value of 0.149, suggesting it does not have a statistically significant impact. The model explains 95.75% of the variation in the data (R-squared), with an adjusted R-squared value of 89.38%, accounting for the number of predictors in the model. The residual error represents the unexplained variation, with a sum of squares of 44.33.

Table:21 Response for Standard Deviations

Level	A	B	C
1	16.50	15.59	21.49
2	21.16	22.24	21.86
3	24.03	26.53	26.16
4	32.04	29.37	24.22
Delta	15.54	13.79	4.67
Rank	1	2	3

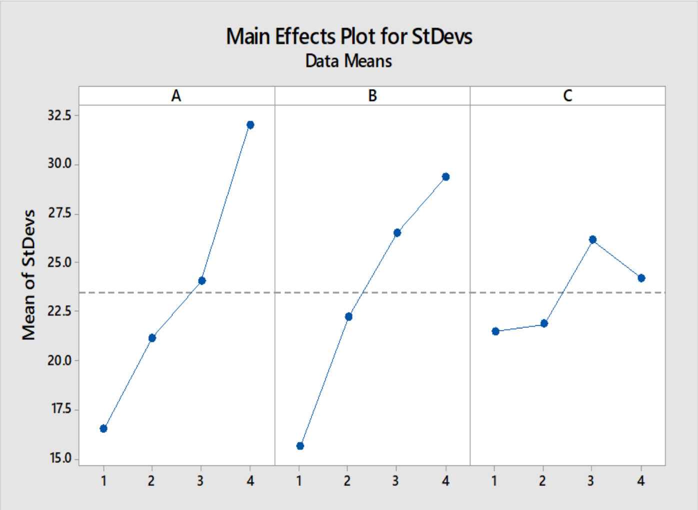

Figure:8 Main effects plot for St Dves

This figure displays the main effects plot for standard deviations (StDevs), showing the mean StDevs at different levels (1 to 4) for factors A, B, and C. For factor A, there is a clear increasing trend, with the mean StDevs rising significantly as the level increases from 1 to 4. Factor B also shows an upward trend, though the increase is less steep than that of A. In contrast, factor C displays a more complex pattern, with a slight increase at first followed by a decrease, indicating a less consistent effect on the variability. This plot helps to visualize how each factor impacts the variation in the data

Table:22 Taguchi Analysis: BSFC, BTE versus A, B, C

Term	Coef	SE Coef	T	P
Constant	23.4337	0.6795	34.484	0.000
A 1	-6.9352	1.1770	-5.892	0.001
A 2	-2.2741	1.1770	-1.932	0.102
A 3	0.5996	1.1770	0.509	0.629

B 1	-7.8454	1.1770	-6.666	0.001
B 2	-1.1917	1.1770	-1.012	0.350
B 3	3.0969	1.1770	2.631	0.039
C 1	-1.9416	1.1770	-1.650	0.150
C 2	-1.5709	1.1770	-1.335	0.230
C 3	2.7287	1.1770	2.318	0.060

This table presents the results of a Taguchi analysis for Brake-Specific Fuel Consumption (BSFC) and Brake Thermal Efficiency (BTE) across factors A, B, and C. The constant term is 23.4337, representing the baseline value. Factor A1 has a significant negative effect with a coefficient of -6.9352 and a p-value of 0.001, indicating its strong influence on the response variable. A2 shows a negative effect but is not significant (p = 0.102), while A3 has a small positive coefficient with a p-value of 0.629, indicating no significant impact. For factor B, B1 has a significant negative effect (p = 0.001), and B2 is not significant (p = 0.350). B3 shows a positive effect with a p-value of 0.039, suggesting a significant contribution. Factor C's terms (C1, C2, and C3) show mixed effects, with C3 approaching significance (p = 0.060).

Table:23 Analysis of Variance for St Devs/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	511.02	511.02	170.339	23.05	0.001	2.7182	95.75%	89.38%
B	3	431.39	431.39	143.796	19.46	0.002			
C	3	57.19	57.19	19.063	2.58	0.149			
Residual Error	6	44.33	44.33	7.388					
Total	15	1043.93							

This table summarises the model's performance by showing the outcomes of an Analysis of Variance (ANOVA) on the standard deviations (StDevs). The response variable is strongly impacted by both A and B, with p-values of 0.001 and 0.002, respectively, indicating that they contribute significantly to the difference in StDevs. In contrast, factor C is statistically insignificant (p=0.149). With a total of 95.75 R-squared and an adjusted R-squared of 89.38%, this model explains 89.38% of the observed data variance when controlling for the total number of predictors. The unexplained variance is represented by the extra inaccuracy, which amounts to 44.33 square.

Table:24 Response for Standard Deviations

Level	A	B	C
1	16.50	15.59	21.49
2	21.16	22.24	21.86
3	24.03	26.53	26.16
4	32.04	29.37	24.22

Delta	15.54	13.79	4.67
Rank	1	2	3

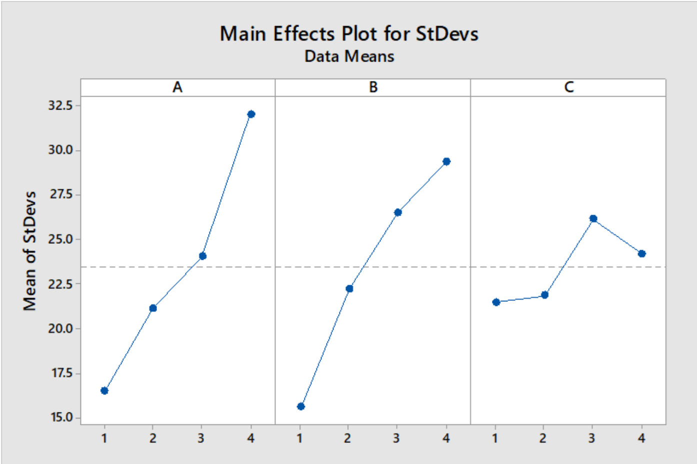

Figure:9 Main effects plot for St Dves

This figure presents the main effects plot for standard deviations (StDevs), illustrating the mean StDevs at different levels (1 to 4) for factors A, B, and C. For factor A, there is a clear increasing trend, with the mean StDevs rising significantly as the level increases from 1 to 4. Factor B also shows a noticeable increase, although the trend is slightly less steep than that of A. Factor C, on the other hand, displays a more irregular pattern with little variation across levels, indicating that the effect of C on StDevs is minimal. This plot helps visualize how each factor influences the variability in the data.

Table: 25Taguchi Analysis: BSFC, BP versus A, B, C

Term	Coef	SE Coef	T	P
Constant	2.92013	0.09220	31.673	0.000
A 1	-0.65739	0.15969	-4.117	0.006
A 2	-0.18769	0.15969	-1.175	0.284
A 3	-0.08233	0.15969	-0.516	0.625
B 1	-1.44033	0.15969	-9.020	0.000
B 2	-0.11822	0.15969	-0.740	0.487
B 3	0.27069	0.15969	1.695	0.141
C 1	-0.06024	0.15969	-0.377	0.719
C 2	-0.04309	0.15969	-0.270	0.796
C 3	-0.07809	0.15969	-0.489	0.642

This table shows the results of a Taguchi analysis for Brake-Specific Fuel Consumption (BSFC) and Brake Power (BP) across factors A, B, and C. The constant term is 2.92013, representing the baseline value. Factor A1 has a significant negative impact with a coefficient of -0.65739 and a p-value of 0.006, indicating its strong effect. However, A2 and A3 are not significant, with p-values of 0.284 and 0.625, respectively. For factor B, B1 shows a significant negative effect with a p-value of 0.000, while B2 and B3 have higher p-values, suggesting weaker or no significant influence. Factor C's terms (C1, C2, and C3) also have higher p-values, indicating they do not significantly affect BSFC or BP

Table:26 Analysis of Variance for St Devs/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	5.3371	5.3371	1.77902	13.08	0.005	0.3688	96.22%	90.56%
B	3	15.2816	15.2816	5.09386	37.46	0.000			
C	3	0.1780	0.1780	0.05933	0.44	0.735			
Residual Error	6	0.8160	0.8160	0.13600					
Total	15	21.6126							

This table presents the results of the Analysis of Variance (ANOVA) for standard deviations (StDevs), summarizing the model's performance. Both factors A and B show highly significant effects on the response variable, with p-values of 0.005 and 0.000, respectively, indicating strong contributions to the variation in StDevs. Factor C, however, does not have a significant impact, with a p-value of 0.735. The model explains 96.22% of the variation in the data (R-squared), and the adjusted R-squared value is 90.56%, accounting for the number of predictors in the model. The residual error represents the unexplained variation, with a sum of squares of 0.8160.

Table: 27 Response for Standard Deviations

Level	A	B	C
1	2.263	1.480	2.860
2	2.732	2.802	2.877
3	2.838	3.191	2.842
4	3.848	4.208	3.102
Delta	1.585	2.728	0.260
Rank	2	1	3

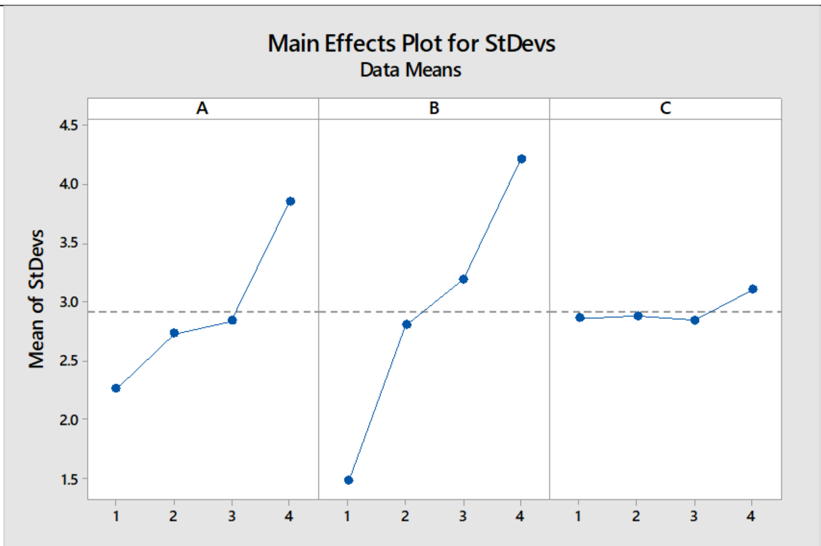

Figure: 10 Main effects plot for St Dves

This figure shows the main effects plot for standard deviations (StDevs), displaying the mean StDevs at different levels (1 to 4) for factors A, B, and C. For factor A, there is a clear increasing trend, with StDevs rising as the levels increase from 1 to 4. Factor B also shows a noticeable increase in StDevs across levels, though the change appears slightly less steep than factor A. Factor C, on the other hand, shows a relatively flat pattern, with little variation across the levels, indicating a minimal effect on StDevs. This plot helps visualize how each factor influences the variability in the data.

Table:28 Taguchi Analysis: BTE, BP versus A, B, C

Term	Coef	SE Coef	T	P
Constant	20.5136	0.7022	29.213	0.000
A 1	-6.2778	1.2163	-5.162	0.002
A 2	-2.0864	1.2163	-1.715	0.137
A 3	0.6819	1.2163	0.561	0.595
B 1	-6.4051	1.2163	-5.266	0.002
B 2	-1.0735	1.2163	-0.883	0.411
B 3	2.8262	1.2163	2.324	0.059
C 1	-1.8813	1.2163	-1.547	0.173
C 2	-1.5278	1.2163	-1.256	0.256
C 3	2.8068	1.2163	2.308	0.060

This table summarizes the results of a Taguchi analysis for Brake Thermal Efficiency (BTE) and Brake Power (BP) across factors A, B, and C. The constant term is 20.5136, representing the baseline value. Factor A1 has a significant negative impact on BTE with a coefficient of -6.2778 and a p-value of 0.002, indicating it is a key factor. A2, however, is not significant ($p = 0.137$), and A3 has a small positive coefficient, also not significant ($p = 0.595$). For factor B, B1 is statistically significant ($p = 0.002$), showing a negative effect, while B2 and B3 have higher p-values, suggesting weaker or no significant impact. Factor C's terms (C1, C2, C3) also show moderate effects, but none are statistically significant, with p-values slightly above 0.05.

Table: 29 Analysis of Variance for St Devs/ Model Summary

Source	DF	Seq SS	Adj SS	Adj MS	F	P	S	R-Sq	R-Sq(adj)
A	3	412.98	412.98	137.661	17.45	0.002	2.8088	94.11%	85.28%
B	3	287.24	287.24	95.745	12.14	0.006			
C	3	56.46	56.46	18.819	2.39	0.168			
Residual Error	6	47.34	47.34	7.890					
Total	15	804.01							

This table presents the Analysis of Variance (ANOVA) for the standard deviations (StDevs), summarizing the statistical performance of the model. Factors A and B have significant effects on the response variable, with p-values of 0.002 and 0.006, respectively. Factor C, however, does not show a statistically significant effect ($p = 0.168$). The model explains 94.11% of the variance in the data (R-squared), with an adjusted R-squared value of 85.28%, accounting for the number of predictors. The residual error, representing the unexplained variation, has a sum of squares of 47.34. The F-values for factors A and B indicate their strong impact on the variability in StDevs.

Table:30 Response for Standard Deviations

Level	A	B	C
1	14.24	14.11	18.63
2	18.43	19.44	18.99
3	21.20	23.34	23.32
4	28.20	25.17	21.12
Delta	13.96	11.06	4.69
Rank	1	2	3

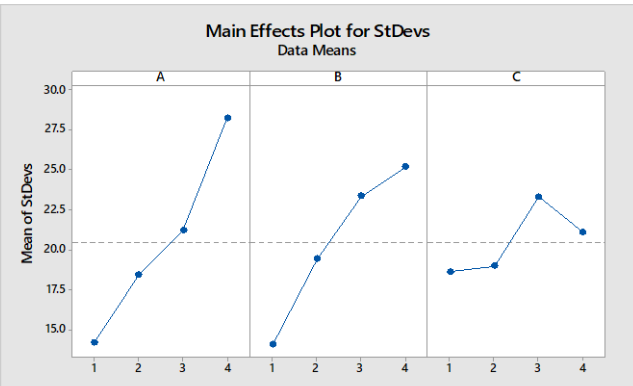

Figure: 11 Main effects plot for St Dves

Table:31 Taguchi prediction for performance

S.NO	A	B	C	S/N Ratio	Mean	St Dev	Ln (St Dev)
1	1	1	1	-0.204902	5.91812	5.94942	2.01177
2	1	2	2	0.0130284	11.6481	11.6346	2.42689
3	1	3	3	-0.851223	17.8256	19.8688	2.93471
4	1	4	4	0.104297	19.3431	19.4905	2.92554
5	2	1	2	-0.577570	9.70438	10.4943	2.31367
6	2	2	1	-0.258961	14.9344	15.4724	2.64902
7	2	3	4	-0.689015	20.1706	21.8558	3.12318
8	2	4	3	-0.702569	24.0706	25.8863	3.26111
9	3	1	3	-1.51161	14.6819	17.5972	2.79007
10	3	2	4	-0.758808	18.9706	20.7244	3.09176
11	3	3	1	-0.845999	20.2194	22.1404	3.07565
12	3	4	2	-0.425356	23.1781	24.3201	3.17991
13	4	1	4	-1.01703	19.7906	22.3932	3.01884
14	4	2	3	-1.23330	26.4619	29.9292	3.46762
15	4	3	2	-0.886294	26.7694	29.4943	3.41785
16	4	4	1	-0.364971	29.2281	30.9669	3.44234

This figure shows the main effects plot for standard deviations (St Devs) across factors A, B, and C. For factor A, there is a clear increasing trend in the mean standard deviations as the levels go from 1 to 4, suggesting a growing variability in the data. Similarly, factor B shows an upward trend, though not as pronounced as A. Factor C displays a more erratic pattern, with a slight increase at first followed by a decrease, indicating less consistent variability across levels. This plot helps visualize the impact of each factor on variability in the data.

5. Conclusions:

This study successfully demonstrated the optimization of diesel engine parameters for Sal seed biodiesel blends to minimize emissions and enhance engine performance. The Taguchi L16 orthogonal array method proved to be an efficient approach, significantly reducing the number of experimental trials while still capturing the key interactions between parameters.

- Engine load had a noticeable effect on emissions and fuel consumption, with higher loads generally increasing emissions.
- Injection pressure played a crucial role in improving fuel atomization, thereby enhancing combustion efficiency and reducing particulate matter emissions. The 200 bar injection pressure was found to be the most effective for minimizing emissions without compromising performance.
- Among the different biodiesel blends tested, B30 (30% biodiesel blend) provided the optimal balance between emission reduction (especially in CO and HC) and engine performance. However, higher biodiesel blends (B50) led to an increase in NO_x emissions, highlighting the need for further tuning of engine parameters to manage this trade-off.

In conclusion, the study provides valuable insights into the potential of Sal seed biodiesel as an alternative fuel in diesel engines, emphasizing the importance of optimizing engine parameters such as injection pressure and biodiesel blend ratios to reduce harmful emissions. The Taguchi method offers a practical, efficient way to identify the best operational conditions for cleaner and more efficient diesel engine performance.

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