SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V11I12P108

Volume 11 Issue 12, 93-102, December 2024

Originial Article

Investigation and Development of Novel Biodiesel Blend Using Response Surface Methodology in C. I. Engine

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Received: 14 October 2024 Revised: 23 November 2024 Accepted: 10 December 2024 Published: 27 December 2024

Abstract - *The limited amount of fossil fuels on the earth and the terrifying prediction of material consumption is a warning bell to sustainability issues. The blending of biodiesel leads to reduce the natural burden. The main aim of this study is to investigate the prediction model of specific fuel consumption using the Response Surface method using a Central Composite Design. The engine run trial is reduced due to the technique because of the response surface methodology's table of readings. Minitab 17, a statistical program, is used for this purpose. Engine performance tests were conducted using a Variable Compression Ratio (VCR) engine with a set compression ratio and a constant speed of 1500 rpm. The transesterification technique was used to create the biodiesel, a unique blend of karanja and jatropha in an equal volume proportion, which was chosen for testing. The engine is operated by a mixture of diesel and biodiesel in different proportions. Three variables were altered for the experiment: blend ratio, injection pressure, and variable load. Blend ratios of 0%, 25%, and 50% by volume with neat diesel were considered. With different loads of 2, 5, and 8 kg, high, medium, and low injection pressures were used. As a result, the experimental findings showed that the output parameter, representing the specific fuel consumption by the Response Surface Method (RSM), correlated with all three input factors. Results were obtained using another mathematical method, namely multiple linear regression, to validate the model. The experimental results were more consistent with the RSM model results.*

Keywords - *Karanja with Jatropha biodiesel, Response surface method, Minitab 17, Specific fuel consumption, Multiple linear regression method.*

1. Introduction

Energy and material usage have widely increased throughout the world. The limited natural resources on earth need to be conserved for future generations. Non-renewable consumption has drastically increased as renewable sources yet are limited in applications [1]. High demands, limited sources, exhaustible in nature, increasing prices, exhaust and emissions, pollution, etc., are a few limitations of conventional fossil fuels, which lead to exploring alternate energy sources [2]. The Indian National Biodiesel Policy allows biodiesel production from non-edible vegetable oils such as karanja, jatropha, and mahua, potential resources for biodiesel production in India as they grow on wasteland [3].

Vegetable oils are quickly turned into biodiesel using one of the most popular transesterification methods, which produces qualities similar to diesel fuel. It is linked to a few issues, including inadequate atomization, fuel filter clogging, and incomplete combustion [4]. Biodiesel contains no sulphur or hydrocarbons, although it does have a higher oxygen concentration than traditional diesel fuel. Thus, biodiesels in fuel mixes improve combustion quality while reducing exhaust emissions [5]. Biodiesel blend can be used without any modification on the vehicular system in internal combustion engines; hence, it is advantageous to utilize the biodiesel fuel in the engine. Most biodiesels revealed potential outcome with equal diesel volume [6]. The role of injection pressure in combination with compression ratio revealed potential outcomes for engine emission characteristics [7]. Similarly, plastic conversion to biodiesel meets ASTM standards regarding physio-chemical properties [8].

2. Literature Review

According to the literature survey, varying injection pressure is difficult and tedious, and there are limited resources for varying injection pressure. Increasing injection pressure improves engine combustion characteristics, but optimization is the key to controlling emissions [2].

Karanja and jatropha were tested in experiments as individual biodiesels at different loads in engine performance tests, and the results appeared satisfactory [9]. Many authors have worked on biofuels and their blends by varying injection pressure. The biodiesel experiments produced using waste cooking oil and diesel fuel was done in five equal stages by varying percentages of biodiesel from

B0 to B100, and engine performance was investigated. Where B0 is pure diesel fuel, and B100 is pure biodiesel, the intermediate blend shows the volume % of biodiesel, and the remaining is pure diesel. For example, B20 shows 20% biodiesel and 80% diesel volume [6]. Biodiesel being a promising alternative fuel, the researcher carried out the pilot study for the production of biodiesel from non-edible oils such as karanja (pongamia pinnata) oil and jatropha (jatrophacurcas) oil [10].

The transesterification procedure allows the biodiesel to be blended with diesel. The yield percentages of biodiesel were determined using flash point (◦C), cloud point (◦C), pour point (◦C), and other fuel parameters. The blended biodiesel satisfied the standards established by the ASTM. The various types of biodiesel possess individual advantages and limitations [11]. Process optimization research was carried out based on catalyst concentration and time to achieve maximum yield. It was determined that the best conditions for achieving the highest yield were 1% catalyst concentration and three hours. Moreover, a high difference was observed in neat and added biodiesel emission characteristics [12].

Oil of karanja and jatropha for biodiesel production by base catalyst method was experimented with by comparing each biodiesel's performance and emission characteristics in a compression engine. It was reported to be appropriate for diesel engine applications. Also, harvesting jatropha is achievable easily and is among the best biodiesel comparatively from an environmental aspect [1], [13].

Biodiesel of karanja, which is 100% fatty acid methyl ester, gives higher efficiency than jatropha, but in the case of blends of jatropha, it gives higher efficiency than others. Jatropha is a superior substitute fuel compared to Karanja in terms of performance and emissions. Jatropha oil has the most decreased emissions and fuel efficiency. However, the exhaust gas temperature of jatropha biodiesel is higher than karanja [5], [9].

Moreover, a lower ratio of karanja showed better emission characteristics with a 20% blend with mineral diesel [14]. The impacts of injection pressure were revealed to be important, as varying injection pressure was reported. The role of fuel injection pressure is prominent in emission characteristics and control [15]. The study reported from Malaysia karanja oil production through the transesterification process showcases that its physio-chemical properties meet the EN14214 standards regarding brake-specific fuel consumption and brake power at 40 blends [16].

The Response Surface Method Multi-linear Regression is a powerful statistical tool investigating the relationship between dependent variables withand This leads to identify a research objective as hybrid novel biodiesel and to be tested for specific fuel consumption through engine performance test with RSM method for optimization of engine run trails.

Table 1. Abbreviations and Nomenclature

SFC	Specific Fuel Consumption
VCR	Variable Compression ratio
B0	Conventional diesel fuel
B25	25 volume% biodiesel, 75 volume% diesel
B50	50 volume% biodiesel, 50 volume% diesel
RSM	Response surface method
MLR	Multiple linear Regression method
BD	Biodiesel mixture of Karanja and Jatropha
IP	Injection pressure in bar
BP	Brake Power in KW
ICE	Internal combustion engine

3. Methodology

The flowchart (Figure 1) shows the process of optimizing output parameters depending on the input parameters. The first step is to define variables and their levels. Three independent input parameters, biodiesel blend, injection pressure and load, are selected for VCR engine performance. The experimental setup selected for performance is a single cylinder 4, stroke VCR engine that runs at a constant speed of 1500 rpm and 3.7 KW power provided with an eddy current dynamometer. Corresponding output parameters SFC and BP are the aim of our research work obtained from actual engine run trials and performed per the Central Composite Design (CCD) method from Minitab 17. Their levels are low, medium and high.

RSM was used to optimize output parameters with the highest desirability. Then, the RSM model for all response parameters is to be analyzed. This paper shows that SFC and BP are responses, and calculated errors indicate the differences between the experimental and predicted parameters. Again, for the MLR model, the same process was followed to get the minimum error of predicted values for each selected parameter. Optimization of output parameters will be done with the help of this flowchart. The two basic steps of RSM and MLR are independent variable selection and their levels and design selection. This leads to the verification of the existing model. RSM from MINITAB 17 was executed, as shown in Figure 1. The flow chart depicts optimizing output parameters depending on the input parameters. Here, the biodiesel was prepared equal to the volume of jatropha and karanja. The new biodiesel prepared for the study is coded as BD in this study. The initial step in RSM was to define variables and their levels.

Three independent input parameters, biodiesel blend, injection pressure and load, were selected for VCR engine performance. Corresponding output parameters were Specific Fuel Consumption (SFC) and brake power (bp), which were the aim of our research work that had to be obtained from actual engine run trials and performed as per Central Composite Design (CCD) [18], [19]. The ANOVA investigates all the independent process-related factors [17]. The CCD design is preferred due to quick first and second order terms and is mostly adopted in RSM due to this advantage.

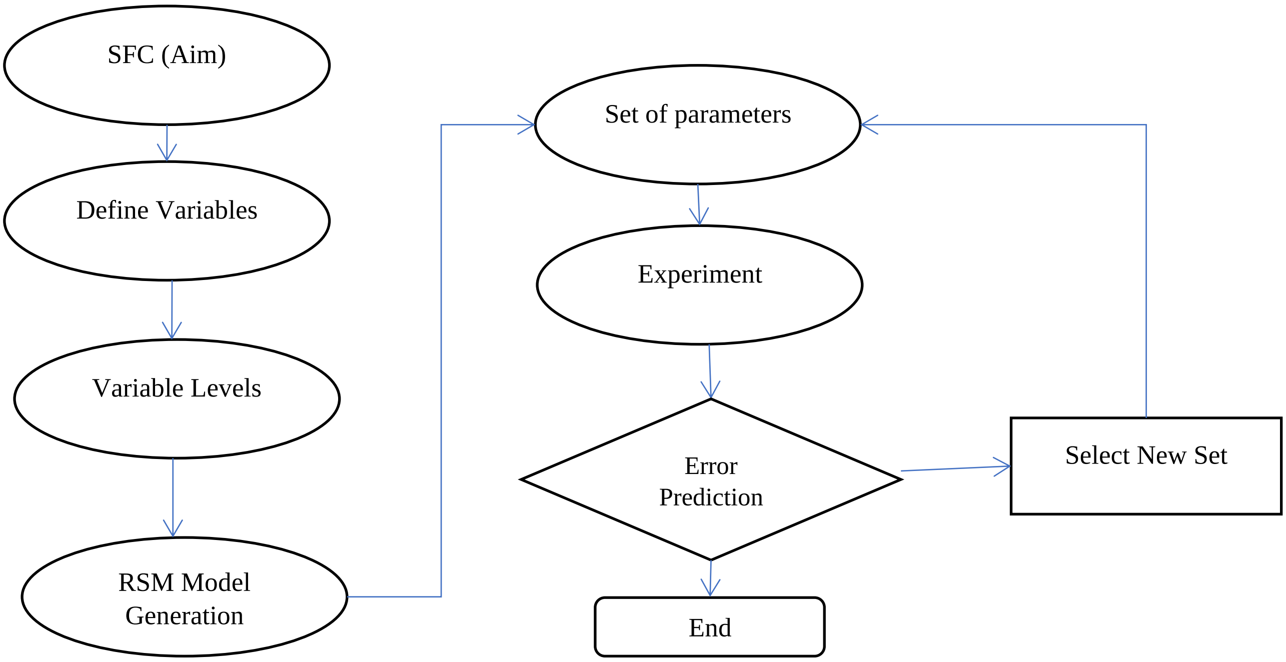

Fig. 1 Flowchart for RSM

Here, Minitab 17 is used. RSM was used for optimized output parameters with the highest desirability and is adopted for each response parameter to be analyzed. This paper shows that SFC and BP are responses, and calculated errors indicate the differences between the experimental and predicted parameters. Furthermore, the multiple linear regression (MLR) method was adopted to check the consistency of RSM. A similar process was followed to get a minimum predicted value error for each selected parameter. This leads to the optimization and verification of the existing model.

Two basic steps of RSM and MLR are independent variable selection and their levels and design selection [18], [20]. The flow process execution is elaborated in steps to obtain the outputs.

The main aim of obtaining specific fuel consumption is based on three parameters: injection pressure, biodiesel blend, and varying loads. Further, to define variables and variable levels, two steps with equations are listed [8], [21]

3.1. Step 1: To Determine Independent Variables with their Levels

The parameters (variables) have major effects on the output. The variables' range must be coded between variables -1 and 1.

The equation for coding appears as

$$X = \frac{x-[x_{max}+x_{min}]/2}{[x_{max}-x_{min}]/2} \tag{1}$$

Where X = coded variable and x = natural variable

x_{max} is the maximum value and x_{min} is the minimum value of the natural variable.

3.2. Step 2: To select the Experimental Design for the Prediction and Verification of the Model Equation

Experimental design is generated from experimental points that execute several runs and blocks. From the model equation, coefficients are predicted. Model test data are compared with predicted data. Statistical method equation, as shown below in equation 2, leads to calculating Root Square Method Error (RSME) and coefficient of multiple determination (R2) as obtained from equation 3

$$\text{RSME} = \left[\frac{1}{n}\sum_{j=1}^{n}\left|a_j - p_j\right|^2\right]^{1/2} \tag{2}$$

$$R^2 = 1 - \left[\frac{\sum_{j=1}^{n}(a_j-p_j)^2}{\sum_{j=1}^{n}(p_j)^2}\right] \tag{3}$$

Here, aj= experimental specific consumption and pj= predicted specific consumption

Table 2. Process variables with their selected ranges

Independent Variables	Symbol		Level	
	Actual	Coded	Actual	Coded
Biodiesel A (%)	BD	X1	0	-1
			25	0
			50	1
Injection Pressure B (bar)	IP	X2	150	-1
			180	0
			210	1
Load C (kg)	Load	X3	2	-1
			5	0
			8	1

In composite central design, the suitable factors are 3 parameters with 3 levels. Continuous 3 independent input design variables selected were biodiesel blend, injection pressure and load, coded values in three levels corresponding to the parameter's actual value. Table 2 displays the selected process variables and their ranges through the Minitab software. Moreover, the letters A, B, and C are assigned to biodiesel, injection pressure, and load for easy coding.

The RSM model is a prepared mathematical model further analyzed to perform experiments and trials on an engine. Data analysis through Minitab-17 and graphical analysis along with the MLR method are used compared to the RSM method, which uses the same parameters. The performance of 15 experimental trials needs to be performed from a regression table generated for 20 sets. SFC and BP obtained from engine run trial and calculations are tabulated in Table 3.

Table 3. Regression table (ANOVA) and experimental readings for SFC and BP

Sr No	BD (%)	IP (bar)	Load (Kg)	SFC (Expt.)	BP(KW) (Expt.)
1	25	180	8	0.20	2.55
2	50	150	8	0.21	2.58
3	50	210	8	0.21	2.51
4	0	150	8	0.23	2.58
5	0	210	8	0.24	2.52
6	0	180	5	0.28	1.48
7	25	150	5	0.28	1.47
8	25	180	5	0.28	1.51
9	25	210	5	0.28	1.49
10	50	180	5	0.28	1.47
11	25	180	2	0.53	0.46
12	50	150	2	0.53	0.45
13	50	210	2	0.55	0.43
14	0	210	2	0.63	0.48
15	0	150	2	0.67	0.44

Table 4. Predicted errors by RSM and MLR for SFC

Sr. No	SFC (RSM)	Error (RSM)	SFC (MLR)	Error (MLR)
1	0.21	0.00	0.16	0.05
2	0.23	-0.02	0.12	0.09
3	0.24	-0.03	0.13	0.08
4	0.24	-0.01	0.19	0.04
5	0.25	-0.01	0.19	0.05
6	0.33	-0.05	0.37	-0.09
7	0.29	-0.01	0.34	-0.06
8	0.29	-0.01	0.34	-0.06
9	0.31	-0.03	0.35	-0.07
10	0.27	0.01	0.31	-0.03
11	0.58	-0.05	0.53	0.00
12	0.54	-0.01	0.49	0.04
13	0.56	-0.01	0.50	0.05
14	0.67	-0.04	0.56	0.07
15	0.66	0.01	0.56	0.11

RSM model for SFC and BP obtained from Minitab 17 are shown in equations 4 and 5, respectively. The values of SFC and their error values are listed in Table 4. The values of BP through RSM are reported in Table 5.

$$\begin{aligned}\text{SFC (RSM)} = {} & 1.517-0.00456\ \text{BD} -0.00624\text{IP} \\ & - 0.1856\ \text{Load} + 0.000025\ \text{BD*BD} + 0.000018\ \text{IP*IP} \\ & + 0.01177\ \text{Load*Load} + 0.000002\ \text{BD*IP} \\ & + 0.000350\ \text{BD*Load} - 0.000014\ \text{IP*Load}\end{aligned} \tag{4}$$

$$\begin{aligned}\text{BP (RSM)} = {} & 0.698+0.00270\text{BD}+0.00449\text{IP} + 0.3674\text{Load} \\ & -0.000022\ \text{BD*BD}-0.000010\text{IP*IP} \\ & + 0.00182\text{Load*Load}-0.000012\ \text{BD*IP} \\ & + 0.000050\ \text{BD*Load}-0.000208\ \text{IP*Load}\end{aligned} \tag{5}$$

Similarly, another method called MLR is used to check the consistency of the RSM method. In a linear regression model, the procedure consists of a scalar dependent variable (Ý) and one or more independent variables (X). Multiple regression equations require more than one independent variable [20]. An MLR equation specifies the relation between a response variable Ý and is obtained as shown in equation 6 based upon input parameters X1, X2, and X3. Where X1 = % of biodiesel, X2 = injection pressure, X3 = load. Further $\hat{Y}$ = predicted value, B0 is the estimated values of y-intercept, B1, B2, and B3 are estimated values of the independent variable coefficient.

The multiple regression equation is as follows.

$$\acute{Y} = B0 + B1X1 + B2X2 + B3X3 \tag{6}$$

The specific fuel consumption and brake power obtained by applying the MLR method are shown in equations 7 and 8 respectively. The value of SFC is plotted in Table 4, and BP obtained is depicted in Table 5. Thus, Tables 4 and 5 compare RSM and MLR methods for SFC and BP.

$$\begin{aligned}\text{SFC (MLR)} = {} & 0.664 - 0.001240\ \text{BD} + 0.000100\ \text{IP} \\ & - 0.06167\ \text{Load}\end{aligned} \tag{7}$$

$$\begin{aligned}\text{BP (MLR)} = {} & -0.1882 - 0.000240\ \text{BD} - 0.000300\ \text{IP} \\ & + 0.34933\ \text{Load}\end{aligned} \tag{8}$$

Table 5. Predicted errors by RSM and MLR for BP

Sr No	BP (RSM)	Error (RSM)	BP (MLR)	Error (MLR)
1	2.54	0.01	2.55	0.00
2	2.55	0.03	2.55	0.03
3	2.47	0.04	2.53	-0.02
4	2.56	0.02	2.56	0.02
5	2.51	0.01	2.54	-0.02
6	1.48	0.00	1.50	-0.02
7	1.49	-0.02	1.51	-0.04
8	1.48	0.03	1.50	0.01
9	1.46	0.03	1.49	0.00
10	1.45	0.02	1.49	-0.02
11	0.45	0.01	0.45	0.01
12	0.42	0.03	0.45	0.00
13	0.41	0.02	0.44	-0.01
14	0.46	0.02	0.45	0.03
15	0.43	0.01	0.47	-0.03

4. Results and Discussion

Comparison of RSM and MLR methods with experimental SFC and BP were obtained through the actual performance of new biodiesel that blended karanja and jatropha. The results obtained by RSM and MLR were compared with actual run trials sequentially to conclude that the selection of RSM was appropriate. Specific significant parameters were also determined from the statistical interference in the ANOVA table. Figures 2 and 3 showcase the comparison of output parameters with experimental and predicted RSM and MLR methods, respectively. The RSM model predicted values are closer to the experimental values than the MLR model. The RSM optimization of biodiesel with pawpaw seed was satisfactory [22]. Similar support for RSM results on optimization of photocatalytic degradation was observed through the adoption of the CCD [23]. The RSM model accuracy is more than 95% for the two response parameters.

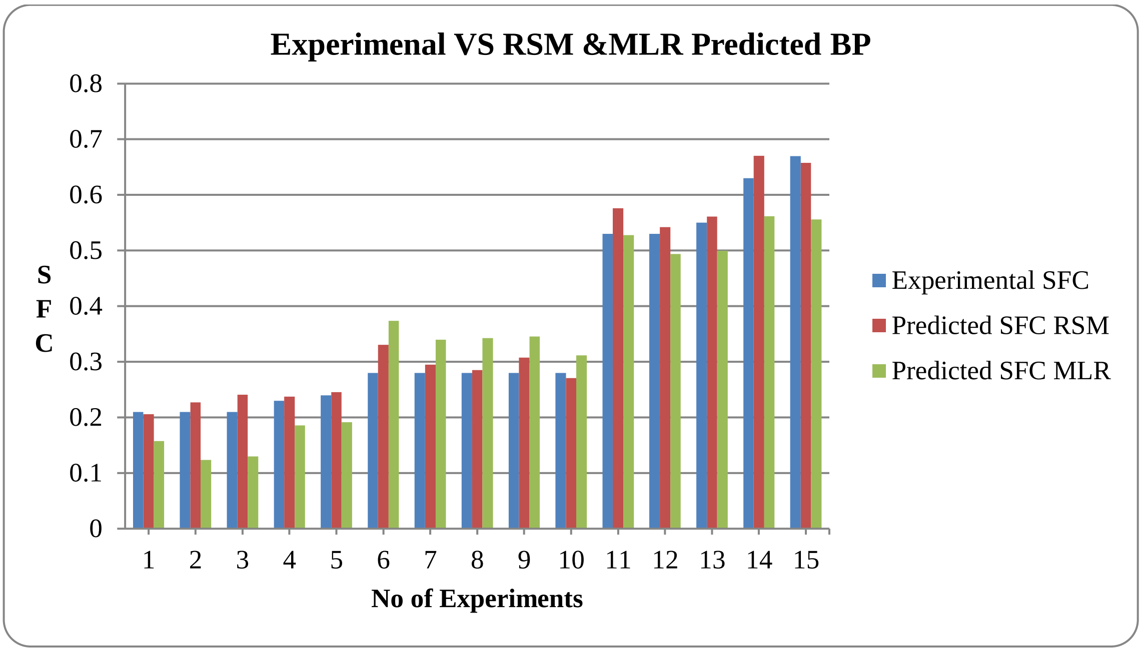

Fig. 2 Experimental and Predicted SFC calculated by RSM and MLR

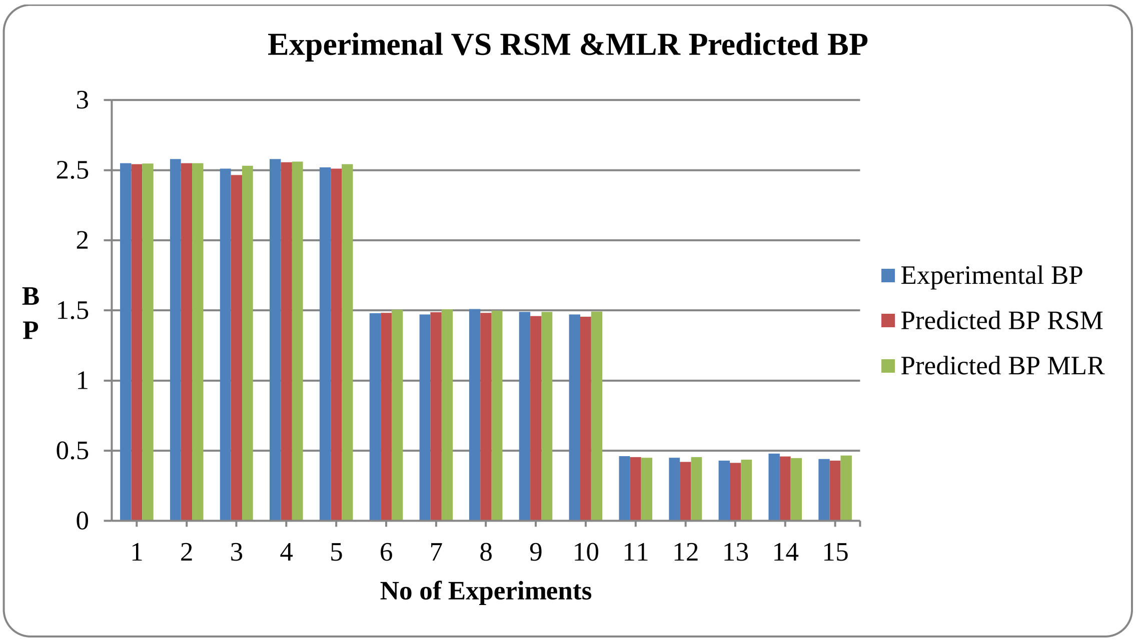

Fig. 3 Experimental and Predicted BP calculated by RSM and MLR

The Anova Table, as shown in Table 6 for specific fuel consumption and brake power with the coefficient of multiple determination and p-value of parameters as shown by the value of R^2, Adj. R^2 and pre-R2 were obtained and tabulated in the results with statistical interference.

Similarly, Table 7 depicts specific fuel consumption and brake power by linear regression is associated with the coefficient of multiple determination and p-value of parameters as shown by the value of R^2, Adj. R^2, and pre R^2. Residual plots for SFC are shown in Figure 4, and BP residual plots in Figure 5.

Table 6. ANOVA for response surface method for SFC and BP

Source of variation	SFC		BP	
	Coeff.	p-value prob.	Coeff.	p-value prob.
Constant	0.27364	0.000	1.50145	0.000
% BD	-0.03100	0.001	-0.00600	0.279
IP, B	0.00300	0.678	-0.00900	0.117
Load, C	-0.18500	0.000	1.04800	0.000
A^2	0.0159	0.262	0.00999	0.202
B^2	0.0159	0.262	0.00999	0.408
C^2	0.0159	0.000	0.01636	1.64
AB	0.00125	0.877	-0.00875	0.166
AC	0.02625	0.007	0.00375	0.537
BC	-0.00125	0.877	-0.01875	0.009
R^2	98.89%		99.98%	
Adj. R^2	97.88%		99.95%	
Pre R^2	91.63%		99.81%	

Table 7. ANOVA of MLR model for SFC and BP

Source of variation	SFC		BP	
	Coeff.	p-value prob.	Coeff.	p-value prob.
Constant	0.664	0.000	-0.1882	0.000
% BD A	-0.001240	0.212	-0.000240	0.392
IP, B	0.000100	0.901	-0.000300	0.206
Load, C	-0.06167	0.000	0.34933	0.000
R^2	79.49%		99.93%	
Adj. R^2	75.64%		99.92%	
Pre R^2	62.62%		99.87%	

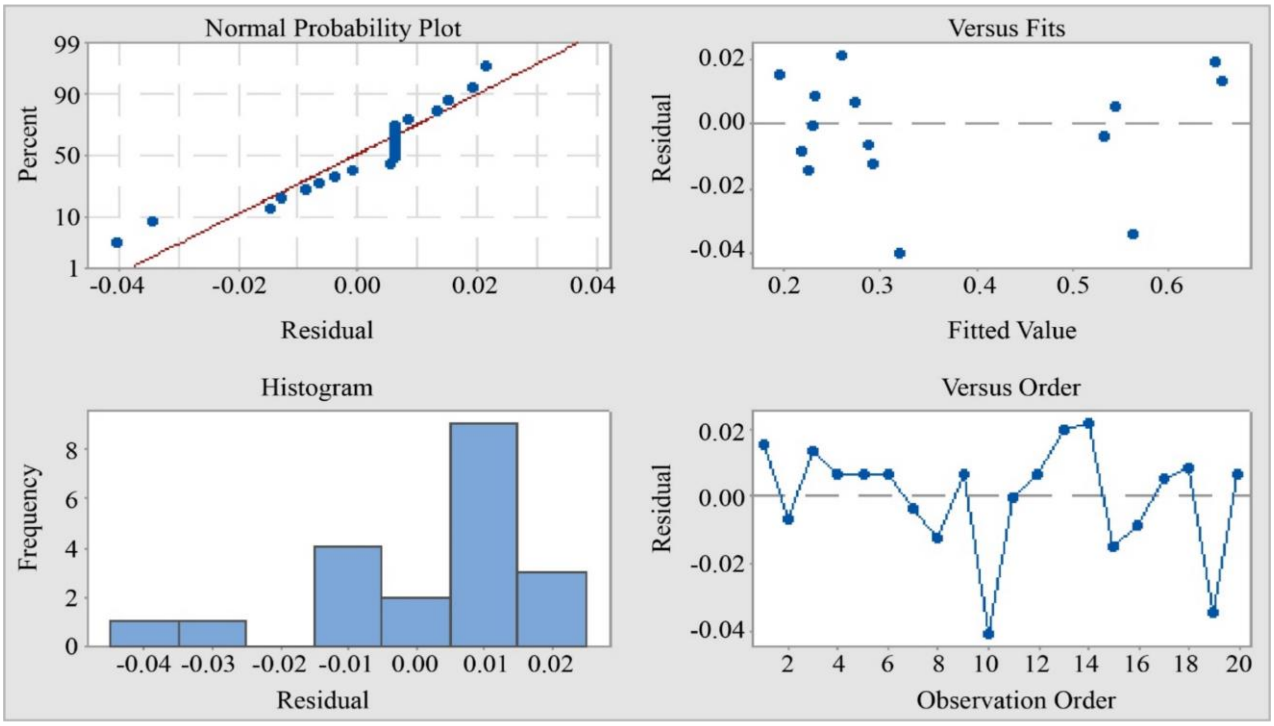

Fig. 4 Residual plots for SFC

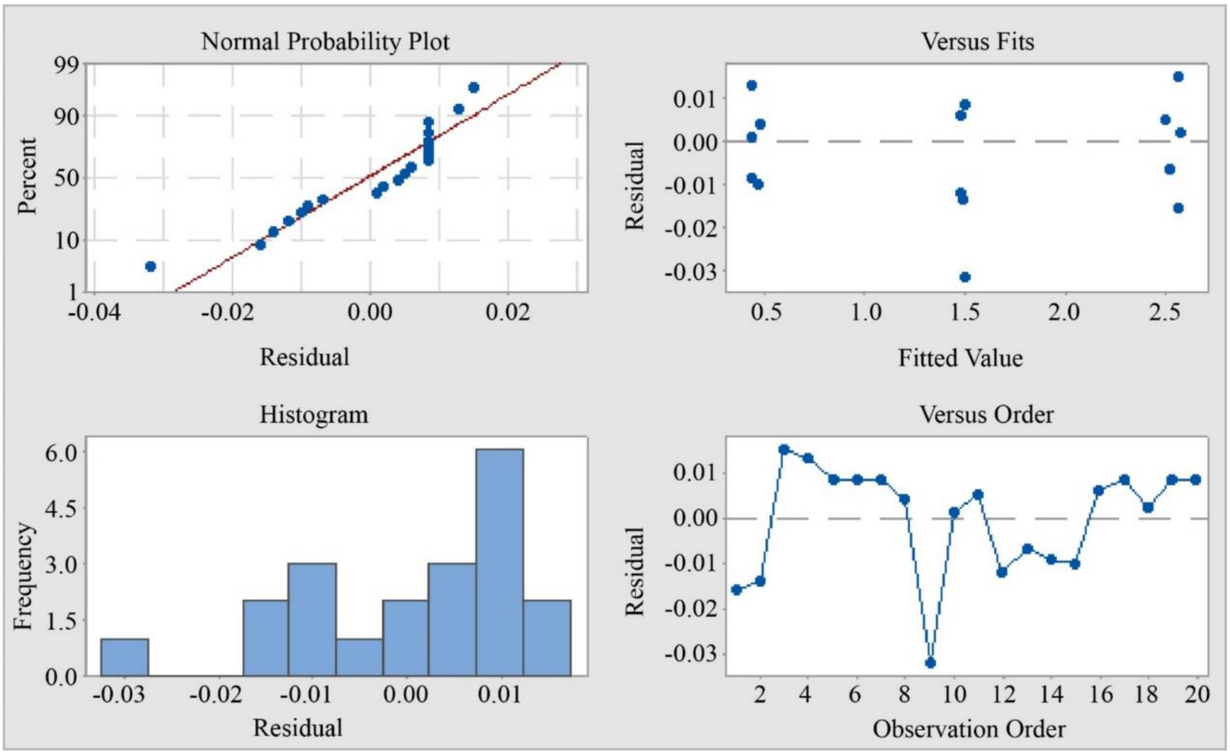

Fig. 5 Residual plots for BP

Figures 4 and 5 show four-in-one residual plots for SFC and BP, respectively. They are used to examine the data for outliers, non-random variation, non-constant variance, and normality.

In a normal probability plot, the residuals roughly follow a straight line, and a roughly symmetrical histogram suggests that the residuals are normally distributed. Since residuals are dispersed randomly, about zero in residuals versus the fitted values, they have constant variance.

There is no undesired consequence because residuals do not show any discernible pattern in the residual versus order plot. The normal probability plot indicated that the prediction of results for the RSM model was close to the straight line. So, the accuracy of the RSM model was higher than the MLR model. No issues with the RSM model are shown by the residuals vs fitted values, continuous histogram plot, and residual versus observation order plot of these residuals.

5. Conclusion

Statistical inferences from RSM response for output parameters align with the experiment's conclusions as follows.

The "Adj R-Squared" of SFC and brake power (KW) are 97.88% and 99.95%, respectively, in realistic conformity with the "R-Squared" R^2 of 98.89% and 99.98% for SFC and BP.

The coefficient of determination (R^2) and adjusted coefficient of determination (R^2 adj) indicated that the estimated model fits the experimental data satisfactorily. A good fit of a model, R^2 should be at least 80 %. The R^2 for these response variables was higher than 80 %, indicating that the regression models explained the mechanism well. Values of "P" less than 0.050 indicate that model terms are significant. In the case of % of biodiesel injection pressure, these are significant model terms. Hence, BD's new biodiesel is prominent. Values of "P" less than 0.050 indicate that model terms are more significant than other parameters.

Predicted values on the response variable were linear in the RSM model compared to the MLR model, which had better accuracy owing to their greater capability. Therefore, the RSM selected and preferred in the case is satisfactory, saving the engine run trials. As shown in Figures 6 and 7 for SFC, the contour and response surface plots reveal that blend is an impacting parameter. SFC first increases with an increase in load and decreases after a point. Similarly, for the blend ratio, SFC initially increases, and then, after a point again, it increases. Thus, SFC at Ip 180 and blend ratio 25 impact, as observed from the analytical and graphical representation, that SFC was at a minimum.

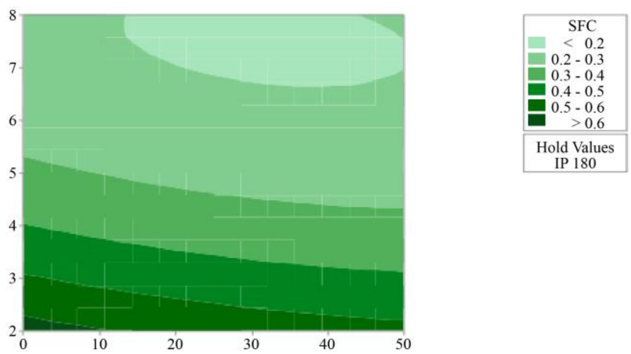

Fig. 6 Contour plots for SFC vs load and biodiesel

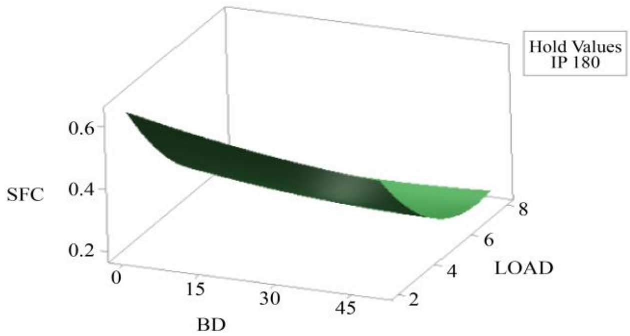

Fig. 7 Surface Plot for SFC vs load and biodiesel

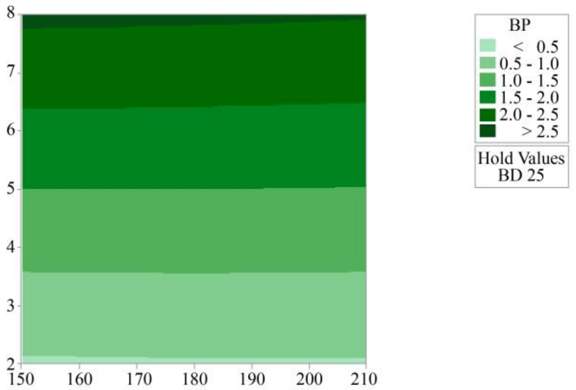

Fig. 8 Contour plots for BP vs load and injection pressure

As shown in Figures 8 and 9, the contour and response surface plots for BP at 025 % BD. It shows that bp increases with an increase in injection pressure.

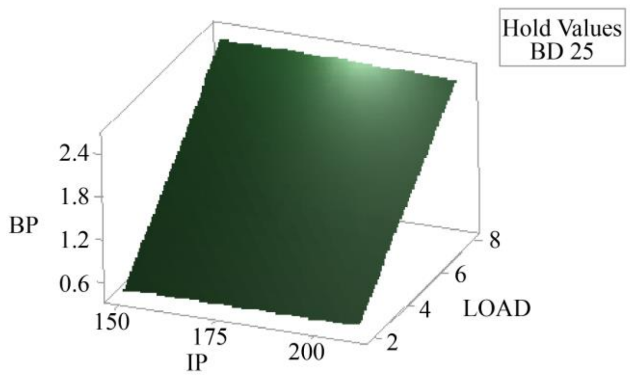

Fig. 9 Surface plot for BP vs load and injection pressure

Finally, Figure 10 depicts the prediction of the RSM model that best fits the model and matches the actual performance of the engine trial. Hence, the results are validated. This study will provide a road map for the researcher and the adoption possibilities of this unique biodiesel blending in CI engines.

Acknowledgment

The authors acknowledge all who helped carry out this work. We also acknowledge editors and reviewers for sparing their valuable time.

Authors Contribution

Each author contributed to conceptualization, framework, and analysis. Both authors have reviewed and submitted the final manuscript.

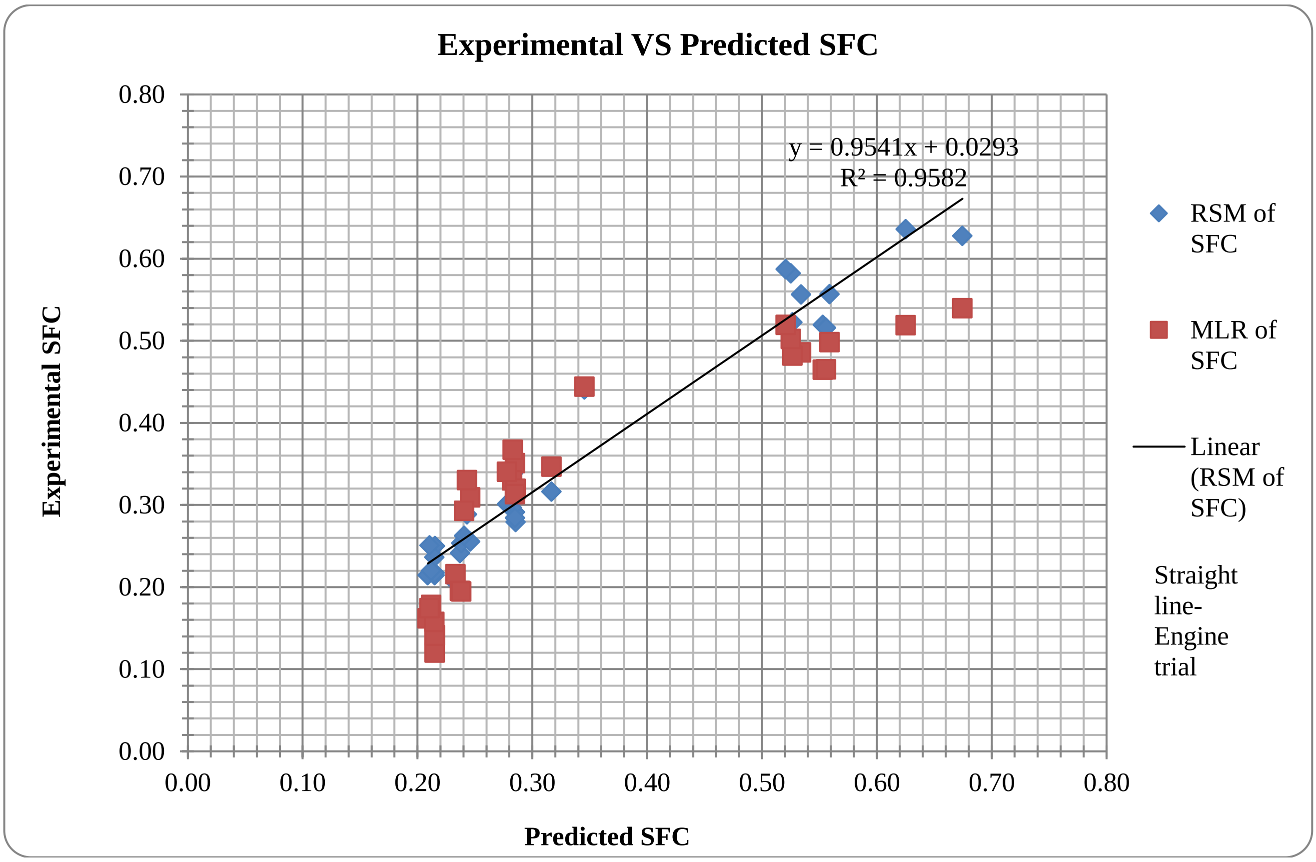

Fig. 10 Final comparison of engine trial with RSM and MLR method

References

[1] Ambarish Datta, and Bijan Kumar Mandal, "Use of Jatropha Biodiesel as a Future Sustainable Fuel," *Energy Technology and Policy*, vol. 1, no. 1, pp. 8-14, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[2] Suat Sarıdemir et al., "Investigating the Role of Fuel Injection Pressure Change on Performance Characteristics of a Di-Ci Engine Fuelled with Methyl Ester," *Fuel*, vol. 271, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[3] Bharat Aher, and Bhushankumar Manmode, "A Review of Performance and Emission Studies in CI Engine Using Biodiesel Obtained from Mixed Feedstock," *IOSR-JMCE 1st National Conference on Recent Innovations in Mechanical Engineering (NCRIME-2018)*, vol. 1, pp. 45-48, 2018. [Publisher Link]

[4] M. Vijay Kumar, A. Veeresh Babu, and P. Ravi Kumar, "Experimental Investigation on the Effects of Diesel and Mahua Biodiesel Blended Fuel in Direct Injection Diesel Engine Modified by Nozzle Orifice Diameters," *Renewable Energy*, vol. 119, pp. 388-399, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[5] B. Deepanraj et al., "Comparison of Jatropha and Karanja Biofuels on their Combustion Characteristics," *International Journal of Green Energy*, vol. 14, no. 15, pp. 1231-1237, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[6] Alireza Shirneshan, and Amin Nedayali, "Investigation of the Effects of Biodiesel-Diesel Fuel Blends on the Performance and Emission Characteristics of a Diesel Engine," *Journal of Technology (Sciences & Engineering)*, vol. 78, no. 6, pp. 169-177, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[7] S. Jindal et al., "Experimental Investigation of the Effect of Compression Ratio and Injection Pressure in a Direct Injection Diesel Engine Running on Jatropha Methyl Ester," *Applied Thermal Engineering*., vol. 30, no. 5, pp. 442-448, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jitendra. K. Baghel et al., "Combine Effect of Injection Pressure and Increasing Inlet Air Pressure on the Performance & Emissions of Ci Engine Using Mahua Oil Blended with Diesel," *International Journal of Advance Engineering and Research Development*, vol. 2, no. 05, pp. 775-784, 2015. [Publisher Link]

[9] P. K. Sahoo, and L. M. Das, "Combustion Analysis of Jatropha, Karanja and Polanga Based Biodiesel as Fuel in a Diesel Engine," *Fuel*, vol. 88, no. 6, pp. 994-999, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[10] G. Jamuna Rani, Y. V. Hanumantha Rao, and B. Balakrishna, "Investigation of Fuel Injection Pressure Impact on Ci Engine Performance and Emissions Using Biodiesel Blend with Alumina Nano Additives," *International Journal of Mechanical Engineering and Technology*, vol. 9, no. 6, pp. 922-928, 2018. [Google Scholar] [Publisher Link]

[11] Santosh Kumar Sahu, and Krishnan Narayanan, "Determinants of Energy Intensity in Indian Manufacturing Industries: A Firm Level Analysis," *Eurasian Journal of Business and Economics*, vol. 4, no. 8, pp. 13-30, 2011. [Google Scholar] [Publisher Link]

[12] M A Asokan, R. Vijayan, and S Senthur Prabu., "A Review on Performance, Emission and Combustion Characteristics of a Diesel Engine Fuelled with Various Vegetable Oil," *Indian Journal of Chemical Technology*, vol. 25, no. 3, pp. 225-234, 2018. [Google Scholar] [Publisher Link]

[13] Sunil Thapa, Natarianto Indrawan, and Prakashbhai R. Bhoi, "An Overview on Fuel Properties and Prospects of Jatropha Biodiesel as Fuel for Engines," *Environmental Technology & Innovation*, vol. 9, pp. 210-219, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[14] Avinash Kumar Agarwa et al., "Effect of Fuel Injection Pressure and Injection Timing of Karanja Biodiesel Blends on Fuel Spray, Engine Performance, Emissions and Combustion Characteristics," *Energy Conversion and Management*, vol. 91, pp. 302-314, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[15] A. Ganguly et al., "A Review on Performance, Emission and Combustion Characteristics of Biodiesel Blends in a Diesel Engine with Varying Injection Pressures," *International Journal of Renewable Energy Research*, vol. 7, no. 4, pp. 2131-2138, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Dewi Harreh et al., "An Experimental Investigation of Karanja Biodiesel Production in Sarawak, Malaysia," *Journal of Engineering*, vol. 2018, pp. 1-8, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jonas Bayuo, Moses Abdullai Abukari, and Kenneth Bayetimani Pelig-Ba, "Optimization Using Central Composite Design (CCD) of Response Surface Methodology (RSM) for Biosorption of Hexavalent Chromium from Aqueous Media," *Applied Water Science*, vol. 10, no. 6, pp. 1-12, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[18] S. Kumar, and R. K. Singh, "Optimization of Process Parameters by Response Surface Methodology (RSM) for Catalytic Pyrolysis of Waste High-Density Polyethylene to Liquid Fuel," *Journal of Environmental Chemical Engineering*, vol. 2, no. 1, pp. 115-122, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[19] Vishal H. Amin, Gaurav P Rathod, and Tushar M Patel, "Parametric Optimization of CI Engine with BThEff by using Coconut Biodiesel and Diesel Blend," *International Journal for Scientific Research & Development*, vol. 3, no. 02, pp. 28-33, 2015. [Google Scholar] [Publisher Link]

[20] Keith A. Marill, "Advanced Statistics: Linear Regression, Part II: Multiple Linear Regression," *Academic Emergence Medicine*, vol. 11, no. 1, pp. 94-102, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[21] Tushar M. Patel, and N.M. Bhatt, "Development of a Mathematical Model of VMS for Automotive Structural Member using FEA-RSM Hybrid Modeling," *Procedia Technology*, vol. 23, pp. 98-105, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[22] Godswill Adizue Ngige et al., "RSM Optimization and Yield Prediction for Biodiesel Produced from Alkali-Catalytic Transesterification of Pawpaw Seed Extract: Thermodynamics, Kinetics, and Multiple Linear Regression Analysis," *Digital Chemical Engineering*, vol. 6, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Il-Hyoung Cho, and Kyung-Duk Zoh, "Photocatalytic Degradation of Azo Dye (Reactive Red 120) in TiO2/UV System: Optimization and Modeling Using a Response Surface Methodology (RSM) Based on the Central Composite Design," *Dyes and Pigments*, vol. 75, no. 3, pp. 533-543, 2007. [CrossRef] [Google Scholar] [Publisher Link]