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COMPARISON OF MLR AND RSM PREDICTION MODEL FOR SPECIFIC FUEL CONSUMPTION OF CI ENGINE FUELED WITH WASTE PLASTIC OIL AND DIESEL BLENDS

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Abstract-*The main objective of the research is to compare the accuracy of Response Surface Methodology (RSM) and Multiple Linear Regression (MLR) model for specific fuel consumption (SFC) for waste plastic oil (WPO) blended with diesel used in single cylinder diesel engine. In study, different blend ratio (100D0B, 50D50B, 0D100B), injection pressure (high, medium, low), load (2 kg, 7 kg, 12 kg), orifice plate diameter (full, low) are considered as input parameters. Response Surface Methodology (RSM) and Multiple Linear Regression (MLR) models were arranged using the results of experiments to predict for specific fuel consumption for waste plastic oil blended with diesel used in a single cylinder diesel engine. The result and comparative data clearly indicate that Response Surface Methodology prediction is more accurate than Multiple Linear Regression prediction.*

Keywords- *Response Surface Method (RSM),Multiple Linear Regression (MLR), Waste plastic oil (WPO), Blend Ratio, Injection pressure, Load, orifice plate diameter*

Nomenclature

RSM : Response Surface Methodology
MLR : Multiple Linear Regression
IP : Injection Pressure
OD : Orifice Plate Diameter
SFC : Specific Fuel Consumption
CCD : Central Composite Design
BR : Blend Ratio (% of diesel + %WPO)
100D0B : 100% Diesel 0% Biodiesel
50D50B : 50% Diesel 50% Biodiesel
0D100D : 0% Diesel 100% Biodiesel

I. INTRODUCTION

Developing renewable energy become an important part of worldwide energy due to the depletion of fossil fuel. The diesel engines are generally used for transportation, engineering industrial and other agricultural machinery due to better fuel efficiency. Alternative fuels for the diesel engines are becoming increasingly important due to the diminishing petroleum reserves and environmental consequences of the exhaust gases from petroleum fueled engines [8]. Now biofuel sources, particularly WPO have attracted much attention as an alternative energy source. It is available everywhere and has proved to be a cleaner fuel and more environment friendly, than the fossil fuels. However, engine test results showed durability problems with WPO because of high viscosity of WPO [1]. To achieve better results with biofuels there is some modification made in input parameters.

II. LITERATURE REVIEW

Kumar et al. (2013) studied about performance and emission exploration of WPO with diesel in CI engine. BSFC increase with increase in WPO blends ratio and decrease with high engine load. The major increase in BSFC is found at 40.43 MJ/kWh on low load and 18.01 MJ/kWh on full load for 10% BWPO. Mechanical efficiency for 10% BWPO is better than diesel fuel on full load condition. CO emission is higher 0.2419 g/kWh on low load to 2.20 g/kWh at the high load. For 40% BWPO as compared to 0.046 g/kWh at low load to 0.86 g/kWh at high load for diesel [1]. **Kumar et al. (2014)** studied about RSM for optimize the process for catalytic pyrolysis of waste high density polyethylene to liquid fuel or modified catalyst. The optimization experimental parameters have been achieved by response surface methodology. An optimization process which reduce number of costly experiments have been successfully attended by RSM method. The optimized value of experimental variables is 450°C. The liquid fuel obtained by catalytic pyrolysis of waste HDPI. At optimized condition consist of petroleum products range hydro carbons (C_{10}-C_{25}) with high heating value (40.17 mg/kg) [2].**Patel et al. (2013)** investigated on to compare the accuracy of artificial neural networks (ANN)and multiple linear regressions model (MLR) model for shear stress of Eicher 11.10 chassis frame. The number of cross members, their locations, cross section and the size of the side and the cross members becomes the design variables. An

ANN and MLR model are developed to predict shear stress of Eicher 11.10 chasis frame. In their study, the results indicate that ANN prediction is more accurate than MLR prediction [11].**Patel et al. (2015)**studied about to compare the prediction accuracy of response surface methodology (RSM) and multiple linear regressions (MLR) model for surface roughness. In their work the effect of burnishing parameters like speed, interference, feed and the surface quality and its wearing characteristics of AL ALLOYS 6061. In their study, they concluded that the RSM approach is a promising tool for accurately estimating surface roughness compare to MLR model & RSM technique is far better than MLR method [10]. **Patel et al. (2015)**studied about to compare the accurateness of artificial neural networks (ANN) and multiple liner regressions (MLR) model for specific fuel consumption for pyrolysis oil blended with diesel used in a single cylinder diesel engine. In their study parameters are injection timing, injection pressure, compression ratio and load are taken. They investigated that the ANN approach is a promising tool for accurately estimating SFC compare to MLR model. They also investigated that ANN technique is better than MLR method [9].**Rinaldini et al. (2017)** studied about performance, emission & combustion characteristics of a direct ignition engine running on WPO. Tests carried out both full and partial load, a diesel engine tested without any modification, running on standard diesel oil and WPO, derived from recycled plastic [4].**Miandad et al. (2017)** studied about the effect of different plastic waste type such as PE, PP, PET and PS. Converting of liquid oil using different past-treatment methods such as blending, distillate reflecting with conventional diesel. All plastic waste types used in experiment have been transformed in to liquefied oil at 450°C The fuel consumption at full load condition decrease using WPO at low speed and increase at high speed. BSFC of WPO is always lower due to the lower density. So, WPO successfully used in direct ignition engine [3].**Patel et al. (2017)** prepared Mathematical model for SFC using RSM in their investigation. CR, IP, engine load, and injection timing have been considered as controlled variables. In their study IP and CR are observed as most inducing variable for SFC [8].**Venkatesan et al. (2017)** investigated on combustion & performance characteristics over DI CI engine which is fueled by blends of WPO. Straight diesel oil blending has been carried at 15% (85 %diesel & 15%WPO) and 30% (70% diesel & 30% WPO) in volume ratio. The BTHE showed minimum differences at part load but enhancement has been noticed at high or full load (30.27%). The BSFC fuels blends at no load and fuel blends at no load & fuel consumption has been reduced as increase in load [7].

III. EXPERIMENTAL SETUP

Figure 1 in single cylinder mutable compression ratios multi-fuel research engine runs with eddy current dynamometer for amendment engine load. In engine Sensor through all parameters like variable pressure, compression air pressure, injection pressure etc. are encoding by “Engisoft” software, installing in computer system. The set-up tactic of the engine is changeable from diesel to Petrol or from Petrol to Diesel with some essential fluctuations. In together modes, the CR can be assorted select of stopping engine & dispossessed of kaleidoscopic the combustion compartment geometry which is especially designed slanting cylinder block planning.

Figure 1. Experiment setup [6]

In both methods, the CR & injection pressure diverse on running of the engine. The setup has stand-alone panel box containing with air box, pressure indicators, two fuel flow quantities and cable for computer interface. Experimental setup has been utilised to analyse engine performance for brake power, frictional power, indicated power, brake thermal efficiency, Mechanical efficiency, indicated thermal efficiency, volumetric efficiency, A/F ratio, SFC, heat balance & combustion analysis. Table 1 shows specification of engine.

Table 1.specification of engine [6]

Number of cylinder	Single Cylinder
Number of Stroke	4
Swept Volume	552.64 cc
Cylinder diameter	80 mm
Stroke length	110 mm
Connecting rod length	234 mm
Orifice Diameter	20 mm
Dynamometer Rotor Radius	141 mm
Fuel	Diesel
Power	3.7 kw
Speed	1500 rpm
Compression ratio range	12 to 18
Injection point variation	0 to 25 Before TDC

IV. EXPERIMENTAL DESIGN

The four parameters deliberated for this study are different blend(WPO), injection pressure (I.P), load and Orifice Plate Diameter. The three parameters are established at three levels each and one parameter set at two levels. The precipitate of the parameters is shown in Table 2.

Table 2.Parameters and Their Level

Parameters	Level				
	(-1)	**(0)**	**(1)**	**(1)**	**(2)**
Blend Ratio (A)	100D0B	50D50B	0D100B	-	-
Injection Pressure (B)	L	M	H	-	-
Load (C)	2	7	12	-	-
Orifice Plate Diameter (D)	-	-	-	full	Half

Experiments is designed rendering to the test circumstances specified by central composite design. The analysis has been piloted for all data sets, with succession parameters levels set as given in Table 4, the values of SFC for all departures are stately using this method. Tentative result for SFC are given in Table 3. Wholly 40 experiments have been channeled to prepare data set for Response Surface Model.

Table 3.Coded values of the variables

Ex No	A	B	C	D
1	0	-1	0	2
2	0	0	0	1
3	0	-1	0	1
4	-1	0	0	2
5	0	0	0	1
6	0	0	0	2
7	0	0	0	2
8	-1	0	0	1
9	0	1	0	2
10	1	0	0	2
11	0	0	1	2
12	0	0	-1	2
13	1	0	0	1

14	0	1	0	1
15	0	0	-1	1
16	0	0	1	1
17	0	0	0	1
18	-1	-1	1	1
19	-1	1	-1	2
20	1	1	1	2
21	1	-1	-1	2
22	-1	1	-1	1
23	1	-1	-1	1
24	-1	-1	1	2
25	0	0	0	1
26	0	0	0	2
27	1	1	1	1
28	0	0	0	2
29	0	0	0	2
30	-1	1	1	1
31	0	0	0	1
32	0	0	0	2
33	1	1	-1	1
34	-1	1	1	2
35	1	1	-1	2
36	-1	-1	-1	1
37	1	-1	1	2
38	1	-1	1	1
39	0	0	0	1
40	-1	-1	-1	2

A, B, C, and D represent coded and real values of various factors.

V. RESULT AND DISCUSSION

5.1. Multiple linear regression analysis

A multiple regression equation is used to definelinear relationship involving more than two variables. A multiple linear regression equation expresses a linear relationship between a response variable y and two or more predictors variable (x1, x2,…, xk). A multiple linear regression model compares the response with the factors which have a strong effect on the performance of a process. The general equation for the proposed second order regression model to predict the response can be written as [10]:

$$SFC = 0.2340 - 0.01700\,A - 0.00600\,B - 0.10200\,C - 0.0160\,D \quad \textbf{(1)}$$

Table 4. Multiple Linear Regression (MLR) Analyzed Data for Specific Fuel Consumption

Term	Coef	SE Coef	T	P
Constant	0.2340	0.0214	10.94	0.000
BLEND	-0.01700	0.00957	-1.78	0.084
IP	-0.00600	0.00957	-0.63	0.535
LOAD	-0.10200	0.00957	-10.66	0.000
OD	-0.0160	0.0135	-1.18	0.245
R-sq =74.62%	R-Sq(pred) =68.17%R-sq(adj) = 77.22%			

Table 4 shows the highest R Square (0.746) and adjusted R square (0.772) values. Hence, as it is discoveredthat formula for the specific fuel consumption is ultimate. From the calculation, we can conclude that the specific fuel consumption estimation formula using Multiple Linear Regression is as shown in equation (1). With the help of Multiple Linear Regression model the value of T-test and respective p-value is presented in table 4.

Factors to be taken into consideration to choose best Equation:

- Use common logic and practical considerations to include or exclude variables.
- Consider the equation with high values of adjusted R-sq.and try including only a few variables.
- Consider the P-value (the measure of the overall significance of multiple regression equation- significance F value) displayed in computer output.
- The smaller P-value is the better.

To check the significance of developed model Analysis of variance (ANOVA) is retained. The p value of 0.000(Table 5), which is less than 0.05 represent the arithmetical significance model. Normal probability plot for experiment proposal are shown in fig. 2 which signify the nearness of prediction with a regression line.

Table 5. Analysis of variance for Specific Fuel Consumption using MLR

Source	DF	SS	MS	F	P
Regression	4	0.217140	0.054285	29.66	0.000
Residual Error	35	0.064060	0.001830		
Total	Total	39			

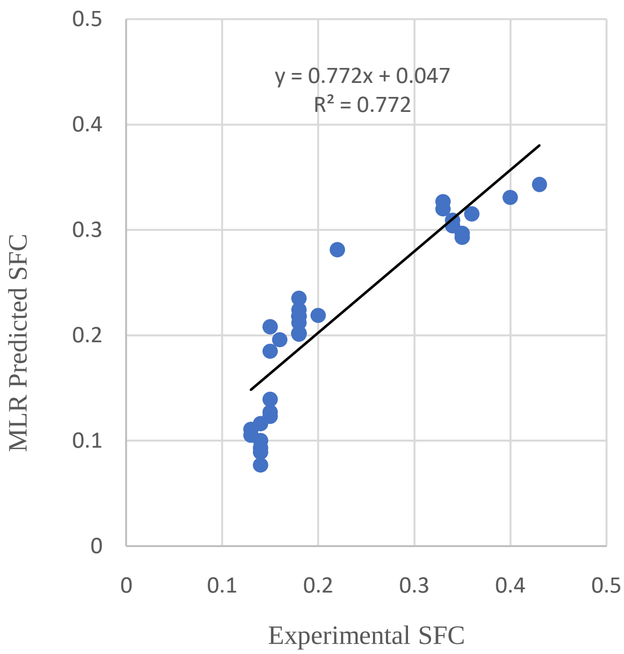

Figure2. Regression plots for SFC using MLR

5.2. Response surface methodology

Experimental model for the Specific Fuel Consumption (SFC), in terms of input parameters, blend ratio, injection pressure, load, orifice plate diameter with three level were developed by using the RSM using Coef value as shown in Table 6. The pooled version of ANOVA for Specific Fuel Consumption (SFC) indicates that the P values for the terms A, B, A*A, B*B, A*B, A*D, B*C, B*D terms are above 0.05 which define its non-significant value. In this case C*C, A*C, C*D are significant model terms. The prediction equation forSpecific Fuel Consumption (SFC)using RSM is as below by eliminating non-significant value. The "Pred R-Squared" of 0.8099 is in reasonable agreement with the "Adj R-Squared" of 0.9341.

$$\text{SFC(coded)} = 0.2488 - 0.0170\,A + 0.0390\,B - 0.2100\,C - 0.0320\,D + 0.00545\,A{*}A - 0.00455\,B{*}B + 0.06545\,C{*}C - 0.00562\,A{*}B + 0.01437\,A{*}C + 0.0000\,A{*}D + 0.00687\,B{*}C - 0.0200\,B{*}D + 0.0480\,C{*}D \quad \textbf{(2)}$$

All the coefficients are to be predictable using experimental data as shown in Table 6.

Table 6.Projected Regression Coefficients Specific Fuel Consumption (SFC) using for RSM

Term	Coef	SE Coef	T-Value	P-Value
Constant	0.2008	0.0116	17.29	0.000
A	-0.0170	0.0154	-1.10	0.280
B	0.0090	0.0154	0.58	0.564
C	-0.1380	0.0154	-8.96	0.000
D	-0.01600	0.00689	-2.32	0.028
A*A	0.00545	0.00929	0.59	0.562
B*B	-0.00455	0.00929	-0.49	0.629
C*C	0.06545	0.00929	7.04	0.000
A*B	-0.00562	0.00545	-1.03	0.311
A*C	0.01438	0.00545	2.64	0.014
A*D	-0.00000	0.00975	-0.00	1.000
B*C	0.00687	0.00545	1.26	0.218
B*D	-0.01000	0.00975	-1.03	0.314
C*D	0.02400	0.00975	2.46	0.021
R-sq.=95.61%	R-sq.(pred)=80.99%R-sq.(adj)=93.41%			

Table 7.ANOVA for Surface Roughness using RSM

Source	DS	SS	MS	F-value	P-value
Regression	13	0.268852	0.020681	43.55	0.000
Linear	4	0.041388	0.010347	21.79	0.000
Square	3	0.043764	0.014588	30.72	0.000
Interaction	3	0.043764	0.014588	30.72	0.000
Residual Error	6	0.007949	0.001325	2.79	0.031
Lack-of-Fit	16	0.012348	0.000772		
Pure Error	10	0.000000	0.000000		
Total	39	0.281200			

The acceptability of model was tested by analysis of variance (ANOVA). Table.7 of ANOVA for SFC shows that the p-value for model is less than 0.05, which suggests that the model is significant. This means that the effect of interference on SFC depends on the load. Non-significant lack-of-fit is required for any model to be fitted.Normal probability plot for experiment proposal are shown in fig. 3 which signify the nearness of prediction with a regression line.

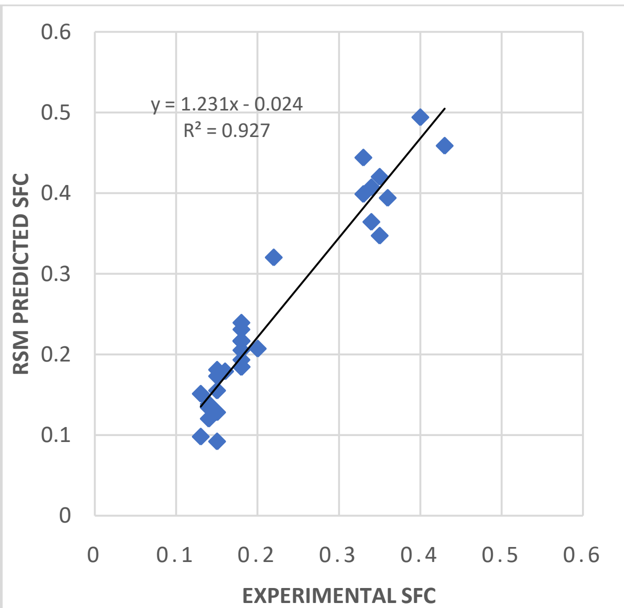

Figure 3.Regression plot for SFC using RSM

5.3. Comparison of MLR and RSM model

In below Table 8 shows MLR and RSM prediction comparison forSpecific Fuel Consumption (SFC). Fig. 2 shows a regression model of MLR and Fig. 3 shows a regression model of RSM. They show that RSM technique is more reasonable in predicting the Specific Fuel Consumptionthan the MLR technique [9]. This might be due to the large amount of data required for developing a sustainable regression model, when the neural network could recognize the relationships with less data for distributed and parallel computing natures. A second reason is the effect of the predictors on the dependent variable, which may not be linear in nature. In other words, the RSM model could probably predict Specific Fuel Consumption (SFC) with a good performance owing to their bettertractability and ability to model nonlinear relationships.

Table 8.MLR and RSM Prediction Comparison Table

Sr No.	A	B	C	D	EXPERIMENTED SFC	MLR PREDECTED SFC	RSM PREDICTED SFC	ERROR MLR	ERROR RSM
1	0	-1	0	2	0.15	0.208	0.18125	-0.058	-0.03125
2	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
3	0	-1	0	1	0.18	0.224	0.19325	-0.044	-0.01325
4	-1	0	0	2	0.2	0.219	0.20725	-0.019	-0.00725
5	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
6	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
7	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
8	-1	0	0	1	0.18	0.235	0.23925	-0.055	-0.05925
9	0	1	0	2	0.16	0.196	0.17925	-0.036	-0.01925
10	1	0	0	2	0.15	0.185	0.17325	-0.035	-0.02325
11	0	0	1	2	0.14	0.1	0.13625	0.04	0.00375
12	0	0	-1	2	0.34	0.304	0.36425	0.036	-0.02425
13	1	0	0	1	0.18	0.201	0.20525	-0.021	-0.02525
14	0	1	0	1	0.18	0.212	0.23125	-0.032	-0.05125
15	0	0	-1	1	0.33	0.32	0.44425	0.01	-0.11425
16	0	0	1	1	0.14	0.116	0.12025	0.024	0.01975
17	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
18	-1	-1	1	1	0.15	0.139	0.09229	0.011	0.05771
19	-1	1	-1	2	0.36	0.315	0.39427	0.045	-0.03427
20	1	1	1	2	0.14	0.077	0.13477	0.063	0.00523
21	1	-1	-1	2	0.35	0.293	0.34727	0.057	0.00273
22	-1	1	-1	1	0.4	0.331	0.49427	0.069	-0.09427
23	1	-1	-1	1	0.34	0.309	0.40727	0.031	-0.06727
24	-1	-1	1	2	0.15	0.123	0.12829	0.027	0.02171
25	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
26	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
27	1	1	1	1	0.14	0.093	0.13877	0.047	0.00123
28	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
29	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
30	-1	1	1	1	0.15	0.127	0.15527	0.023	-0.00527
31	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
32	0	0	0	2	0.18	0.202	0.1848	-0.022	-0.0048
33	1	1	-1	1	0.35	0.297	0.42029	0.053	-0.07029
34	-1	1	1	2	0.13	0.111	0.15127	0.019	-0.02127
35	1	1	-1	2	0.22	0.281	0.32029	-0.061	-0.10029
36	-1	-1	-1	1	0.43	0.343	0.45877	0.087	-0.02877
37	1	-1	1	2	0.14	0.089	0.13427	0.051	0.00573
38	1	-1	1	1	0.13	0.105	0.09827	0.025	0.03173
39	0	0	0	1	0.18	0.218	0.2168	-0.038	-0.0368
40	-1	-1	-1	2	0.33	0.327	0.39877	0.003	-0.06877

Therefore, in the condition of data sets with a limited number of observations in which regression models fail to capture certainly, advanced soft computing approaches like RSM may be preferred.

VI. CONCLUSIONS

The present investigation aimed at the comparison of MLR and RSM model for Specific Fuel Consumption prediction. This optimization is carried out by developing Specific Fuel Consumption models based onthe table of random readings is created in arithmetical software Minitab 17Minitab. Response Surface Methodology (RSM) and Multiple Linear Regression (MLR) models were arranged using the results of experiments to predict for specific fuel consumption for waste plastic oil blended with diesel used in a single cylinder diesel engine. The comparative study of MLR model and the RSM model for Specific

Fuel Consumption prediction draws the following conclusions.

- With the help of generated predicted model of SFC optimum set of parameters can be found out for better SFC. It is found that model is significant and sufficient to represent relationships between the variable and response.
- The results obtained during preliminary test suggest that Response Surface Methodology (RSM) approach is a correctly estimating SFC compare to Multiple Linear Regression (MLR) model.
- The result and comparative data clearly indicate that Response Surface Methodology (RSM) prediction is more accurate than Multiple Linear Regression prediction (MLR).

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