An application of design of experiments approach to statistically model and optimize performance parameters of a single cylinder four-stroke diesel engine

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Abstract*: *This paper investigates the application of design of experiments to enhance the performance characteristics such as indicated thermal power and mechanical efficiency of a four-stroke diesel engine with single cylinder. The dependent response variables are examined by varying the independent variables namely engine speed from 1421 to 1435 rpm, load from 18 to 28 kg and fuel flow rate from 2.5 to 3 kg/h. The influence of the input parameters and their interactions on the response functions are quantified using mathematical models. Statistical analysis comprising of analysis of variance, residuals, Pareto and normal probability are used for validating the models and obtaining relevant parameters. Engine load is proved to be the most significant factor influencing the indicated thermal power while fuel flow rate considerably impacts the mechanical efficiency. The optimum settings of the input variables are determined to be engine speed of 1435 rpm, load 28 kg and fuel flow rate 2.5 kg/h. The indicated thermal power is maximized to 6.3187 kW whereas mechanical efficiency has been increased to 80.0775 percent with the optimum settings.

***Keywords*: Diesel engine, full factorial design of experiments, optimization, analysis of variance**.

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I. INTRODUCTION

In today's revolutionary world, internal combustion (IC) engines have become indispensable for human society for a variety of applications including electricity generation, vehicle engines and domestic generators [1]. The IC engines with four-stroke spark ignition (SI) and compression ignition (CI) are the most commonly used. Several approaches including the experimental method are adopted for enhancing engine efficiency and performance as well as optimizing specific fuel usage. The approach of experimental technique involves evaluating only one factor at a time (OFAT). The method becomes complicated when a large number of factors are examined at the same time and effect of factors' interactions are to be analyzed. Because of these restrictions, understanding and optimizing the system performance is challenging. Moreover, laboratory research findings, which are applicable to only one set of input variables allows the least scope for replication. The Full Factorial Design of Experiments (FFD) overcomes these limitations of experimental analysis. The method (DOE) is a scientific approach to systematic design and execution of experiments [2]. An array of elements is investigated simultaneously and interactions among the factors and their effects on the system's behavior are determined. To determine the effect of individual elements and their interactions on response functions, mathematical models are constructed. The current study uses FFD to improve the performance responses of a single cylinder four-stroke diesel engine namely indicated thermal power (ITP) and mechanical efficiency (η_{mech}). As such, relevant literatures involving analysis and improvement of IC engines' performance are studied to obtain a thorough understanding of various DOE techniques and statistical approaches used.

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The performance and emission parameters of direct injection diesel engine are optimized using FFD [1, 3] by examining the effect of input variables viz. engine load, compression ratio (CR) and fuel blend on the responses. Effects of exhaust gas recirculation (EGR) and injection timing on performance and emission characteristics of a direct injection diesel engine are investigated using FFD [4]. The performance of four-stroke diesel engine fueled with biodiesel blends is simulated experimentally with numerical model validation [5]. Important CI engine responses such as emission concentrate, fuel consumption and ITP are optimized with regression analysis and statistically significant independent factors are determined. Emission characteristics namely HC, CO and NO_x percent at different operating conditions are investigated for non-road small spark-ignition engines using statistical analysis [6]. The Taguchi method of DOE is applied to reduce emissions and economize fuel consumption in direct injection single cylinder CI [7], where effect of various control variables are analyzed. This DOE technique is also used in optimizing diesel engine performance in which diesel fuel blended with producer gas is used [8]. The combustion efficiency and emission characteristics of a dual fuel CI engine are optimized using FFD [9] by examining various fuel injection variables such as flow rates, injection quantity, time of dwell and others. The emission characteristics and performance of a single cylinder four-stroke CI engine is optimized using DOE approach like grey relational analysis [10, 11] and FFD [12]. The key input parameters analyzed are namely type of fuel blend, blend and CR, injection timing and various others to optimize the responses [11, 12]. The sodium hydroxide-catalyzed synthesis of fatty acid ethyl esters as fuel blend for the engine is optimized using FFD with two replications [12].

From the literature survey, it is concluded that various DOE techniques are deployed in the analysis of diesel engines by predominantly examining fuel blends and exhaust emission. However, only a few studies catered to application of FFD to optimize ITP and η_{mech} performance of a diesel engine. Hence in this research work engine load (w), speed of the engine (s) and fuel flow rate (m_f) are varied to maximize the engine performance parameters. The effects of these input variables and their interactions on engine performance are mathematically correlated. Statistical analysis including variance, Pareto, normal probability and residual were applied for determining significant parameters and model validation.

II. METHODOLOGY

A. Experimental setup

Figure 1 shows a four-stroke diesel engine experimental set up where the FFD experiments of the present work are carried out. It is a single-cylinder water-cooled diesel engine with a maximum power rating of 5 HP, rated maximum speed of 2000 rpm, stroke length of 110 mm and bore diameter 87.5 mm.
The engine's oil sump is filled with lubricant oil (SAE-40) until the indicator level of the dipstick. Clean lubricant is poured when the level of oil in the sump dips below the indicator.

The test fuel used in the engine is commercially graded diesel oil. The fuel tank was filled with diesel oil for carrying out the experiments. The fuel oil was injected to the engine cylinder at 23^{o} before top dead center (BTDC) at an injector pressure of about 220 bar. The fuel delivery valve was closed to allow fuel to pour from the burette while its volume was measured for determining the quantity of fuel consumed. The diesel fuel used in the experiment has a calorific value of 44000 kJ/kg and density of about 780 kg/m^3.

Fig.1. The test engine set up

A fixed CR of 17.9 was maintained throughout for conducting the experiments. The engine's performance was estimated from the experiments by varying three input parameters namely w, s and m_f within the specified ranges (Table 1). The engine was driven for a few minutes at zero load to stabilize its functioning. The load was applied under steady state operations of the engine.

The following equations [13] are applied to calculate the engine's ITP and η_{mech}:

$$\mathrm{Brakepower(BP)} = \frac{2\pi \mathrm{NT}}{60 * 1000}(\mathrm{kW})\#(1)$$

$$\mathrm{Torque\ (T)} = \mathrm{Load} * 9.81 * \mathrm{R_e}(\mathrm{Nm})\#(2)$$

$$\mathrm{Mass\ flow\ rate\ of\ fuel}\ (\mathrm{m_f}) = \frac{x}{t} * \frac{\rho_f}{10^6}(\mathrm{kg/s})\#(3)$$

$$\mathrm{Indicated\ thermal\ power\ (ITP)}\ = \frac{P_{\mathrm{ip}}LAnK}{60 * 1000}\#(4)$$

$$\mathrm{Mechanical\ efficiency}\ (\eta_{mech}) = \frac{\mathrm{BP}}{\mathrm{IP}}\#(5)$$

B. Full factorial design of experiment

In this study, the complete or full factorial DOE methodology is used. An FFD is a statistical experiment consisting of two or more independent variables called factors with each factor having a pair of distinct possible values termed as 'levels' [14]. The number of potential combinations of designed experiments with three factors and two levels of the FFD is 2^3= 8.

a) Fixing the regression coefficients:

The response variable (Z) [15] for n independent variables is represented by a linear regression polynomial (6)

$$Z = q_0 + \sum_{i=1}^{n} q_i x_i + \sum_{i,j=1,j\neq i}^{n} q_{ij} x_i x_j + \sum_{i,j,k=1,k\neq j\neq i}^{n} q_{ijk} x_i x_j x_k\ \#(6)$$

Where, Z represents the responses ITP and η_{mech}. The regression coefficients are denoted by $q_0, q_{\mathrm{i}}, q_{\mathrm{ij}}, q_{\mathrm{ijk}}$ while the independent factors are denoted by x_i, x_j and x_k. For three variables, (6) is rewritten as (7).

$$\mathrm{Z} = q_0 + q_1X_1 + q_2X_2 + q_3X_3 + q_{12}X_1X_2 + q_{13}X_1X_3 + q_{23}X_2X_3 + q_{123}X_1X_2X_3\#\quad(7)$$

Where, X_1, X_2 and X_3 represents the independent input variables w, s and $\mathrm{m_f}$ respectively.
In terms of responses (ITP and η_{mech}) and input variables (7) is rewritten as (8) and (9) respectively.

$$\mathrm{ITP} = q_0 + q_1\mathrm{w} + q_2\mathrm{s} + q_3\mathrm{m_f} + q_{12}\mathrm{ws} + q_{23}\mathrm{sm_f} + q_{31}\mathrm{m_f w} + q_{123}\mathrm{wsm_f} \# (8)$$

$$\eta_{mech} = q_0 + q_1\mathrm{w} + q_2\mathrm{s} + q_3\mathrm{m_f} + q_{12}\mathrm{ws} + q_{23}\mathrm{sm_f} + q_{31}\mathrm{m_f w} + q_{123}\,\mathrm{wsm_f} \# (9)$$

C. *Obtaining the L_8 orthogonal array and design matrix*

Table 1 shows the high and low levels of each of the controllable variables w, s and $\mathrm{m_f}$ considered in the FFD.

Table 1. Factors of full factorial DOE

Factors	Low Level	High Level
Engine load, w (kg)	18	28
Engine speed, s (rpm)	1421	1435
Fuel flow rate, $\mathrm{m_f}$(kg/h)	2.5	3

The L_8 orthogonal array for 2^3 FFD with two levels and three factors [16] is represented in Table 2

Table 2. L_8 orthogonal array

Treatment combination	I	P	Q	PQ	R	PR	QR	PQR
1	+1	-1	-1	+1	-1	+1	+1	-1
p	+1	+1	-1	-1	-1	-1	+1	+1
q	+1	-1	+1	-1	-1	+1	-1	+1
pq	+1	+1	+1	+1	-1	-1	-1	-1
r	+1	-1	-1	+1	+1	-1	-1	+1
pr	+1	+1	-1	-1	+1	+1	-1	-1
qr	+1	-1	+1	-1	+1	-1	+1	-1
pqr	+1	+1	+1	+1	+1	+1	+1	+1

The '+1' and '-1' in Table 2 denotes the high and low ranges for each input parameter. The primary factors P, Q and R symbolizes the input variables s, w and $\mathrm{m_f}$ respectively whereas PQ, PR, QR and PQR reflect the interaction between the essential elements. (1), p, q, r, pq, pr, qr, pqr describe the arrangement of the treatments. This results in the FFD's eight designed experiments. The design matrix of the 2^3 FFD in Table 3 shows the eight designed experiments obtained using the statistical solver MINITAB (version 18) [13].

D. *FFD and test results*

The eight designed experiments (Table 3) were physically performed in the test engine set up (Fig. 1). Equations (1) to (5) are used to determine the responses ITP and η_{mech} for each planned experiment (Table 3). For each designed experiment, three test runs were carried out under identical settings and mean of the responses were calculated. For each test run, test results of five consecutive cycles were recorded and averaged to include cycle to cycle differences.

Table 3 Design matrix for 2^3 FFD with the responses

FFD							Responses	
Order of experiments				Input Factors				
Std. order	Run order	Centre pt.	block	s (rpm)	w(kg)	$\mathrm{m_f}$ (kg/h)	ITP (kW)	η_{mech}(%)
1	1	1	1	1421	18	2.5	3.79	79.50
2	2	1	1	1435	18	2.5	5.42	79.65
3	3	1	1	1421	28	2.5	4.91	79.94
4	4	1	1	1435	28	2.5	6.34	80.07
5	5	1	1	1421	18	3	4.19	75.20
6	6	1	1	1435	18	3	4.21	75.30
7	7	1	1	1421	28	3	4.65	77.34
8	8	1	1	1435	28	3	5.22	77.54

III. RESULTS AND DISCUSSION

A. Obtaining the regression equations

The factorial fits for ITP and η_{mech} describing the effects and coefficients of the independent parameters and their interactions are obtained (Tables 4-5).

Table 4. Factorial fit showing the effects and coefficients for ITP versus its input parameters

Effects and Coefficient for ITP (estimated)		
Factors	Effects	Coefficients
Constant		4.841
s	0.9125	0.4562
w	0.8775	0.4388
m_f	-0.5475	-0.2737
s*w	0.08750	0.04375
s*m_f	-0.6175	-0.3088
w*m_f	-0.14250	-0.07125
s*w*m_f	0.18750	0.09375

Table 5. Factorial fit showing the effects and coefficients for η_{mech} versus its input parameters

Effects and Coefficients for η_{mech} (estimated)		
Factors	Effects	Coefficients
Constant		78.07
s	0.14500	0.07250
w	1.3100	0.6550
m_f	-3.445	-1.722
s*w	0.02000	0.01000
s*m_f	0.005000	0.002500
w*m_f	0.8800	0.4400
s*w*m_f	0.03000	0.01500

Replacing the coefficients in (8) and (9) with the ones obtained in Tables 4 and 5, the regression models for the responses are obtained as represented by (10) and (11) respectively.

$$\mathrm{ITP} = 4.841 + 0.4562\,s + 0.4388\,w - 0.2737 m_f + 0.04375\,s*w - 0.3088\,s*m_f - 0.07125\,w*m_f + 0.09375\,s*w*m_f \quad \#(10)$$

$$\eta_{mech} = 78.07 + 0.07250\,s + 0.6550\,w - 1.722 m_f + 0.01000\,s*w + 0.002500\,s*m_f + 0.4400\,w*m_f - 0.01500\,s*w*m_f \quad \#(11)$$

B. Variance analysis and model fitting

The main factors that impact the responses cannot be established from the factorial fits. Variance analysis or analysis of variance (ANOVA) of the effects (Tables 6 and 7) are conducted at 5% level of significance to determine the significant parameters that influence the responses. Before carrying out the variance analysis, the sparsity of effects principle [15] is applied to remove the insignificantly relevant 3-way interactions from the models (10 and 11).

In variance analysis the subsequent insignificant terms having p-values greater than 0.05 are eliminated one at time and modified ANOVA for each response is obtained. The first insignificant term that is removed from the model of the response ITP is the interaction s*w (p-value = 0.722) followed by w*m_f having p-value of 0.433. The modified ANOVA obtained after eliminating the irrelevant terms is displayed in Table 6. It is observed (Table 6) that the parameter s is the most important factor influencing the response ITP, followed successively by the factors w, m_f and interaction s*m_f, each having p-value less than 0.05. In the ANOVA of the response η_{mech}, the most insignificant term is s*m_f with a p-value of 0.895, subsequently followed by the interaction s*w (p-value = 0.451). The revised ANOVA after discarding the insignificant terms is established (Table 7) with the important parameters (p-value <0.05). It is noticed that the relevant terms impacting the response η_{mech} are w, m_f, interaction w*m_f and s, all having p-values less than 0.05.

The improved regression models for ITP and η_{mech} after variance analysis are obtained (12 and 13). The models are checked for 'goodness of fit' using the coefficient of determination or R^2 value ranging from 0 to 100 %. R^2 is a statistic that provides a measure of closeness of the model with those of the observed outcomes [17]. Adjusted R^2 (Adj. R^2) indicates the corrected goodness of fit obtained with revised variance analysis. The model of ITP has a satisfactory R^2 and Adj. R^2 (Table 6), indicating good fit. The R^2 value of 97.31% complements well with the Adj. R^2 value, explaining that the 93.72% variation is only due to the significant terms that actually influence the response. Similarly, in case of the response η_{mech}, the R^2 and Adj R^2 values are 99.99% and 99.98% (Table 7) respectively signifying good fit of the linear regression.

Table 6. Variance analysis for ITP

Term	Effect	Coef.	SE Coef.	T-Value	p-Value
Constant		4.8413	0.0725	66.75	0.000
S	0.9125	0.4562	0.0725	6.29	0.008
W	0.8775	0.4388	0.0725	6.05	0.009
m_f	-0.547	-0.273	0.0725	-3.77	0.033
s*m_f	-0.617	-0.308	0.0725	-4.26	0.024
S =0.205132		R^2 =97.31%		Adj.R^2=93.72%	

Table 7. Variance analysis for η_{mech}

Term	Effect	Coef.	SE Coef.	T-Value	p-Value
Constant		78.067	0.012	7429.39	0.000
S	0.145	0.0725	0.010	6.90	0.006
W	1.3100	0.6550	0.0105	62.33	0.000
m_f	-3.445	-1.722	0.0105	-163.92	0.000

$w*m_f$	0.8800	0.4400	0.0105	41.87	0.000
S =0.0297209		R^2 =99.99%		Adj.R^2=99.98%	

$$ITP = 4.841 + 0.4562\ s + 0.4388\ w - 0.2737 m_f + 0.04375\ s * w\ - 0.308\ s * m_f \#(12)$$

$$\eta_{mech} = 78.0675 + 0.0725\ s + 0.6550\ w + -1.7225\ m_f + 0.44\ w * m_f \#(13)$$

C. Model validation and standardized residual analysis:

The refitted models (12) and (13) are validated for presence of errors using residual analysis. The normal probability plot of residuals of ITP and η_{mech} are shown in Figs 2(a) and 2(b) respectively. The residuals of the performance models are normally distributed as noticed from the figures. Figures 3(a) and 3(b) further reveal that the errors related to the models are randomly distributed with constant error variances. The residual analysis thus substantiates that the models satisfactorily fit the experimental data.

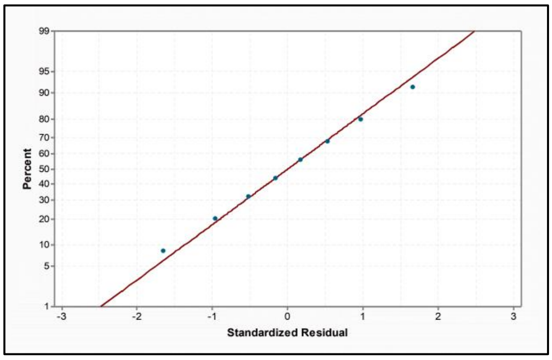

Fig. 2 (a). Normal probability plot of residuals for ITP

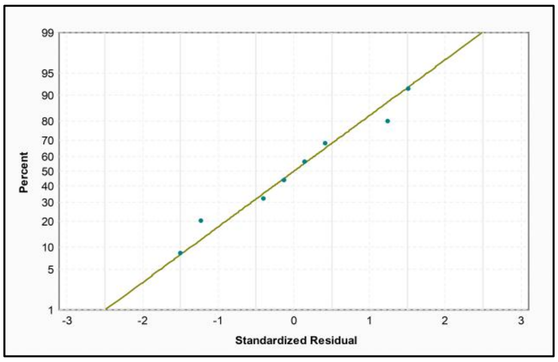

Fig. 2. (b) Normal probability plot of residual for η_{mech}

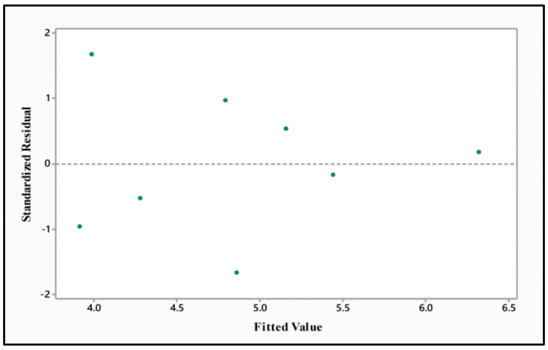

Fig. 3(a). Scatter plot of residual for ITP

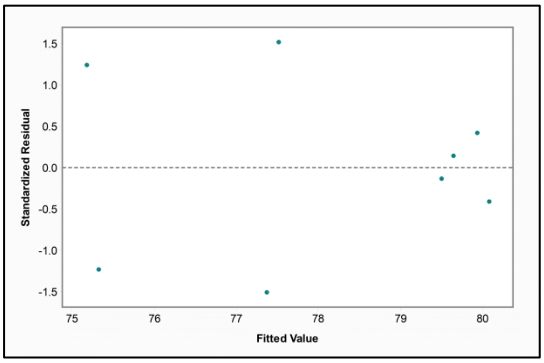

Fig. 3(b). Scatter plot of residual for η_{mech}

D. Establishing the significant parameters

The important parameters that influence the responses are determined from the analysis of Pareto and normal probability plots; whereas the analysis of effect plots (main effect and interaction effect) provides the qualitative effect of the parameters and their interactions on the responses. [16]

a) Pareto analysis of the effects :

The factor effects on responses ITP and η_{mech} are examined in the form of Pareto plots as shown in Figs 4(a) and 4(b). In Fig 4(a), the independent variable s is the most significant factor for ITP whereas, w, $s*m_f$ and m_f are the subsequent important ones. It is revealed from fig 4(b) that the most notable element for η_{mech} is m_f , followed successively by the terms w, interaction $w*m_f$ and s.

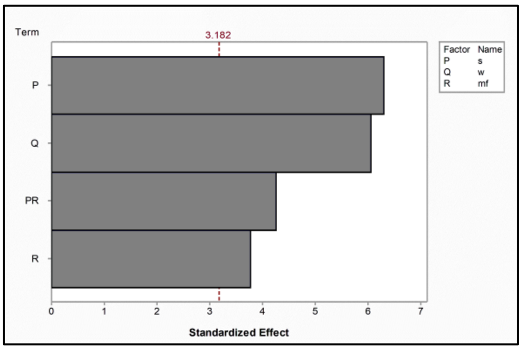

Fig. 4(a). Pareto chart of the effects for ITP

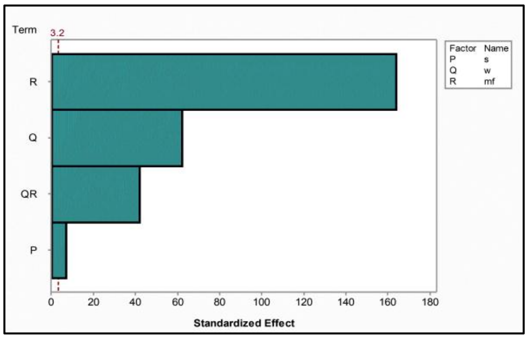

Fig. 4**(b).** Pareto chart of the effects for η_{mech}

b) Normal probability plot for the effect estimates

The normal probability plots of the effects' estimates of responses ITP and η_{mech} are shown in Figs. 5(a) and 5(b). From fig 5(a), it can be asserted that the most statistically significant element is s followed by w, both having a positive effect on the response ITP. Whereas the factor m_f and interaction s*m_f are significant although, but have a negative impact on ITP. In fig 5(b), m_f is the most vital parameter for η_{mech} but negatively impacts the response, whereas the subsequent important ones are factor w, interaction w*m_f and factor s, all of which have positive influence on the response.

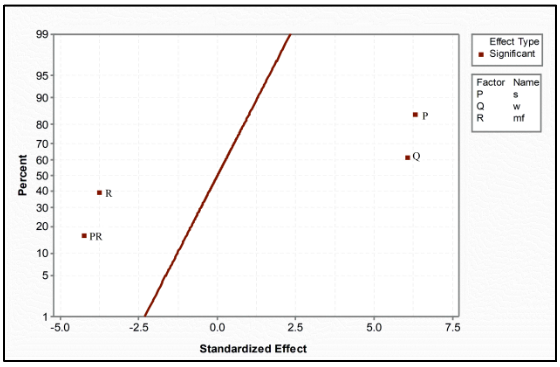

Fig. 5(a). Normal probability plots of effects for ITP

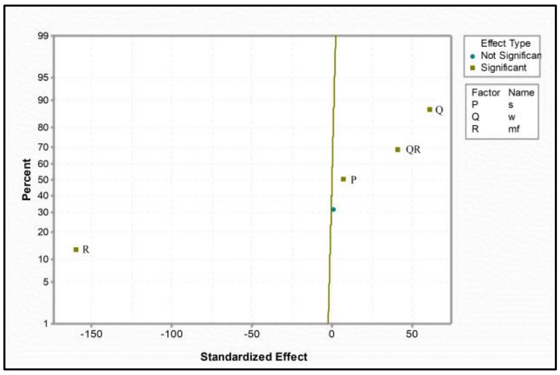

Fig. 5(b). Normal probability plots of effects for η_{mech}

c) Effect plot for responses:

Figures 6(a) and 6(b) show the main effects' plots for the responses ITP and η_{mech} respectively. It is evident from the figures that with increase in w, the responses ITP and η_{mech} increase whereas the responses decrease with increase in m_f as indicated by the downward slopes. The effect of increase in s significantly increases ITP whereas the upsurge in s does not have any noticeable impact on η_{mech}. The interaction effects' plot for ITP in fig 7(a) highlights the fact that the only apparent interaction for the response ITP is s*m_f whereas in the plot for η_{mech} (fig. 7(b)) it is noticed that the interaction w*m_f has marginal relevance on the response.

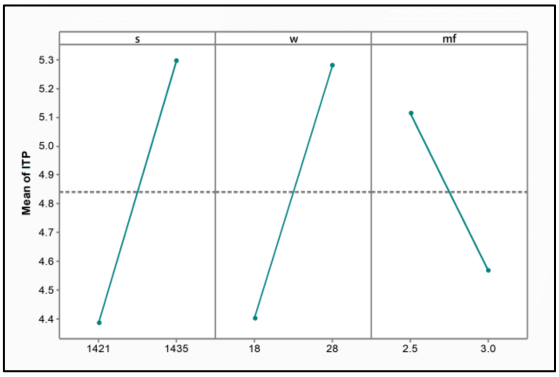

Fig. 6(a) Main effect plot for ITP

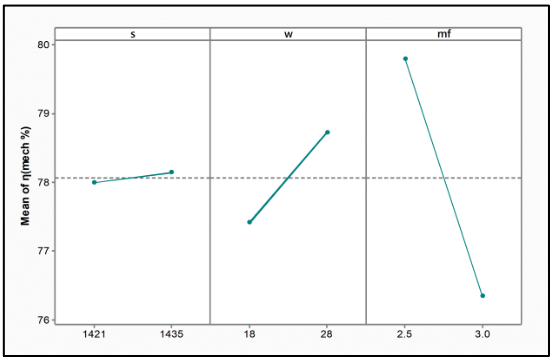

Fig. 6(b). Main effect plot for η_{mech}

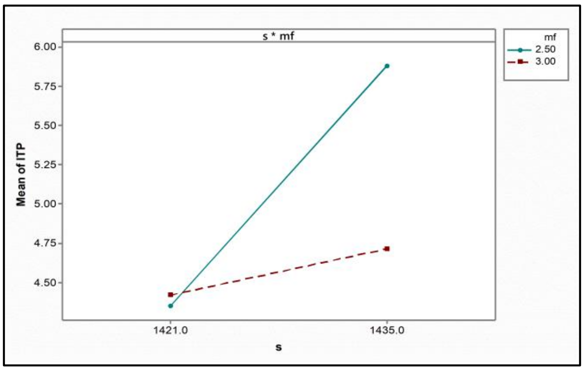

Fig.7(a). Interaction effect plot for ITP

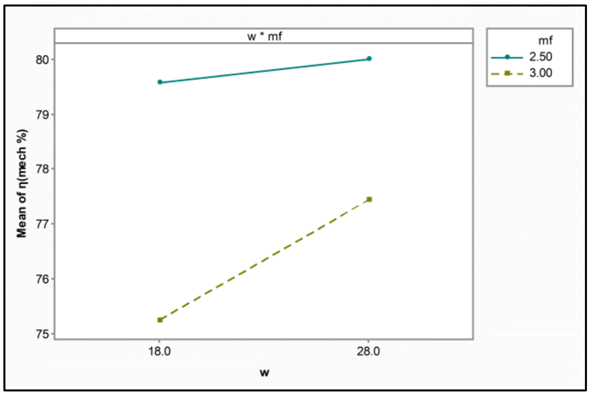

Fig.7(b). Interaction effect plot for η_{mech}

E. Optimized settings

The optimum values of the parameters s, w and m_f to maximize ITP and η_{mech} are obtained (fig 8). The optimum values of the factors are s = 1435 rpm, w = 28 kg and m_f = 2.50 kg/h. The maximum responses, thus obtained with the optimum values are: ITP = 6.3187 kW and η_{mech} = 80.0775 %.

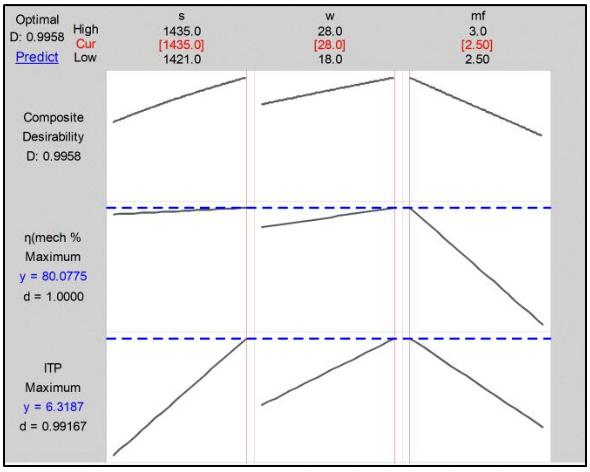

Fig. 8. Plot of Optimal responses

IV. Conclusion

The performance output parameters of a single cylinder four-stroke diesel engine are examined using full factorial design of experiments. The input factors namely engine load, engine speed and fuel flow rate are altered simultaneously and their effects on the responses ITP and η_{mech} are observed. The significance of the input variables is quantified from variance analysis at a significance level of 5%. Pareto and normal probability plots are used to qualitatively examine the influence of the parameters and their interactions. The factor engine speed has the greatest influence on the response ITP followed by the elements load, interaction of engine speed and fuel flow rate ($s*m_f$), and fuel flow rate. In case of the response η_{mech}, the most significant parameter is fuel flow rate while the subsequent factors that impact the response are load, interaction of load and fuel flow rate, and engine speed. The optimum settings for each constituent are established and mathematical models are developed. The model predicted that maximum ITP and η_{mech} are attained at optimum values of 28 kg load, 1435 rpm speed and 2.5 kg/h fuel flow rate. The indicated thermal power is maximized to 6.3187 kW whereas mechanical efficiency is increased to 80.0775% with the optimum settings. The errors associated with the models are within the acceptable limit as the residuals follow normal distribution with constant variance indicating well fit of the regression models.

Nomenclature

R_e	Arm length =172 mm
ρ_f	Density of diesel= 820 kg/m^3
P_{imp}	Indicated mean effective pressure (N/m^2)
L	Length of the stroke (mm)
A	Area of piston (m^2)
N	Speed in revolution per minute,
N	Number of power stroke per minute=N/2(four-stroke engine)
K	Number of cylinders
CV	Calorific value of diesel (42 MJ/kg)
$\frac{x}{t}$	Mass flow rate in (cm^3/min)

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