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Analysis of I.C Engines Based On Fuel Consumption & Vibration

K.udaya sri, Dr.B.S.N.Murthy, Dr. N. Mohan Rao

Abstract— Present days internal combustion engines plays important role. The classical approaches are limited for checking of some measurable output variables and does not provide a deeper insight and usually do not allow a fault diagnosis. Advanced methods of supervision fault detection and fault diagnosis become important for many technical processes, for the improvement of reliability, safety and efficiency. Fuel consumption and vibration signals are being able to be used for monitoring the conditions of internal combustion engines. Most of the conventional methods for fault diagnosis using acoustic and vibration signals are primarily based on observing the amplitude differences in the time or frequency domain. Unfortunately, the signals caused by damaged elements, such as those buried in broadband background noise or from smearing problems arising in practical applications. In the present study, a Response surface methodology technique with analysis of various approaches is proposed to identify the fuel consumption and vibration signals for fault diagnosis in an internal combustion engine. Experiments are carried out to evaluate the engine system for fault diagnosis under various conditions. The experimental results indicate that the proposed technique is effective in the fault diagnosis of an internal combustion engine

Index Terms— anova table,compression ratio,fuel combustion,internal combustion engine,respone surface methodology ,Doppler vibrometer ,vibrations

1 INTRODUCTION

An internal combustion engine (ICE) is a heat engine where the combustion of a fuel occurs with an oxidizer (usually air) in a combustion chamber that is an integral part of the working fluid flow circuit. In an internal combustion engine the expansion of the high-temperature and high-pressure gases produced by combustion apply direct force to some component of the engine. The force is applied typically to pistons, turbine blades, or a nozzle. This force moves the component over a distance, transforming chemical energy into useful mechanical energy. The internal combustion engine, abbreviated as "ICE," is widely used multi-rotating-shaft machinery that is intended to be operated at a wide range of conditions. Computerization has taken place deeply in modern "ICE," which, on the one hand, adds new significance of computer technology and automation in this field. On the other hand, the classical mechanics can no longer deal with such advanced "ICE." Many researchers have been working in the diagnosis field, where they propose different methods and techniques. The general framework of any diagnosis techniques consists of three steps: First, some distinctive information of the fault needs to be acquired. Second, useful features are extracted using a certain tool. Finally, the different faults are identified using a pattern recognition technique. Diagnosis is based on some information acquired and gathered from the system. This information reflects the status or condition of the running "ICE."Most of the methods in this field use various sensors mounted all around the "ICE" for this purpose

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Most engine faults can be classified into two categories: combustion faults and mechanical faults. Misfire is a very common combustion fault for internal combustion (IC) engines and many works have been put forward to study vibration-signal-based misfire diagnosis. For the misfire diagnosis, the vibration based condition monitoring can be further divided into two types: one is based on the translational acceleration signals measured on the engine block, while the other is based on the torsional vibration signal of the crankshaft. Owing to increased dynamic forces from excessive wear and larger clearances at the piston/cylinder wall interface and the journal/bearing interface, piston slap faults and big end bearing knock faults are considered to be two critical mechanical faults in engines. Many researchers have studied the mechanism of piston slap; in general, the aims of these works were focussed on the piston design, including the geometrical and lubrication aspects. Meanwhile, many works have also been devoted to the dynamic response of the journal bearings with non-negligible clearance in the IC engine (slider-crank mechanism). But only a limited number of researchers have investigated the technology of using the measured vibration signals for the diagnosis/prognosis of piston slap faults and bearing knock faults. Moreover, when these vibration-based techniques are applied in a real situation, the faults cannot automatically be diagnosed from the analyzed vibration signals. Artificial Neural Network (ANN) techniques should be a potential solution to the problem of automated diagnostics of different faults in IC engines. Much research has shown that ANNs are a very efficient method to differentiate various faults of rotating machines. A critical issue with ANN applications in machine condition monitoring is the network training, and it is neither likely nor economical to experience a suffi-

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cient number of different actual faults, or generate them in seeded tests, to obtain sufficient experimental results for the network training. Simulation is proving to be a viable way of generating data to train neural networks to diagnose and make prognosis of faults in machines. Very little has been done on simulation of faults in IC engines, primarily limited to combustion faults, which had been shown to affect the torsional vibrations of the crankshaft

1.1 Literature Review

M.R.Parate and S.N.Dandare [1] proposed model-based approach for fault diagnosis of IC engine using audio signals from engine. The audio signals are captured from the engine using microphone and are processed using MATLAB to find characteristics parameters of the signals. Artificial Neural Network is used to identify the fault in IC engine.E.G.Laukonen et al. [2] said certain engine faults can be detected and isolated by examining the pattern of deviations of engine signals from their nominal unfailed values & compare the fuzzy identifier to a nonlinear ARMAX technique and provide experimental results showing the effectiveness of our fuzzy identification based failure detection and identification strategy.Wu yihu et al [3] said a method for diagnosis of misfire fault in internal combustion engine based on exhaust density of HC, CO2, O2 and the engine's work parameters. Rough sets theory is used to simplify attribute parameter reflecting exhaust emission and conditions of internal combustion engine and in which unnecessary properties are eliminated. Mnaouar Chouchane and Ezzeddine Ftoutou [4] said unsupervised clustering is applied for the detection of fuel injection faults of an internal combustion Diesel engine using vibration signals measured on the engine bloc.
BINH Le Khac and TUMA J [5] phase modulation signal is derived from the phase of an analytical signal which evaluated by using the Hilbert Transform technicque. To verify the signal analysis technique, the engine model created originally by John J. Moskwa needs to be extended to produce fluctuation of the crankshaft angular acceleration and to implement the extended model into the dSPACE equipment to control and diagnose the IC engine. M.R.Parate and S.N.Dandare [6] said the incipient faults in IC engine can be detected by conventional methods using various sensors.P.S.Sivasakthivel and R.Sudhakaran [7] focused on the effect of machining parameters such as helix angle of cutter, spindle speed, feed rate, axial and radial depth of cut on temperature rise in end milling. A source code using C language was developed to do the optimization. The obtained optimal machining parameters gave a value of 0.173 °C for minimum temperature rise.M. Subramanian et al. [8]. Experiments were conducted through response surface methodology experimental design.. The second order mathematical model in terms of machining parameters was built up to predict the vibration amplitude and ANOVA was used to verify the competency of the model.Chih-Cherng Chen et al. [9] discussed the vibrations on the cutting tool have a momentous influence for the surface quality of work piece with respect to surface profile and roughness during the precision end-milling process. Singular spectrum analysis (SSA) is a new non-parametric technique of time series analysis and forecasting. Rajesh Kumar Bhushan [10] discussed Optimization in turning means determination of the optimal set of the machining parameters to satisfy the objectives within the operational constraints. The regression models, developed for the minimum tool wear and the maximum MRR were used for finding the multiresponse optimization solutions.M S Packianather and P R Drake [11] describes the use of response surface methodology (RSM) to model the performance of a neural network.D Dhupal et al. [12] discussed the high-intensity pulsed Nd:YAG laser has the capability to produce both deep grooves and microgrooves on a wide range of engineering materials such as ceramics, composites, and diamond.Morteza Ghaffarpour et al. [13] discussed today, tailored welded blank sheets have found various applications in automotive, aeronautic and many other industrial fields.
Bhuvnesh Bhardwaj et al. [14] discussed an attempt has been made to develop a more accurate surface roughness prediction model using response surface methodology based on center composite rotatable design with Box–Cox transformation in turning of AISI 1019 steel. Bhuvnesh Bhardwaj et al. [15] discussed experimental investigation on AISI 1019 steel for study of surface roughness in end milling operation using carbide inserts. Jian Chen, Robert Randall et al. [16] discussed An Artificial Neural Network (ANN) based automated system was developed to diagnose a range of different faults in internal combustion (IC) engines, including combustion faults (misfire) and mechanical faults (piston slap and bearing knock). S. N. DANDAREA and S. V .DUDUL [17] says Fault detection has gained growing importance for vehicle safety and reliability. Aina T et al. [19] discussed the need to improve the performance characteristics of the gasoline engine have necessitated. Increasing the compression ratio below detonating values to improve on the performance is an option.Experimental values show that there is agreement between the theoretical and experimental performance characteristics of the engine.Yousef Shatnawi and Mahmood Al-khassaweneh [20] proposed an effective and automated technique to diagnose the faults, the emitted sound signal of the "ICE" is exploited as the information carrier of the faults, wavelet packet decomposition is used as the feature extraction tool, and finally, extension artificial neural network is used for the classifications of the extracted features. S. N. Dandarea and Dr. S. V .Dudulb [21] done the deals with the problem of fault detection in an automobile engine using acoustic signal,optimal Artificial Neural Network has been designed for the best performance.Sandeep Kumar Yadav and Prem Kumar Kalra [22] discussed a signal analysis technique for internal combustion (IC) engine fault diagnosis based on the spectrogram and artificial neural network (ANN). Okafor A. A et al. [23] discussed an engine test experiment was carried out using engine test bed.
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2. METHODOLOGY

2.1 ANOVA

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ANOVA or analysis of variance is used to evaluate the difference in average scores measured on a continuous scale among one or more characteristics defined by categories. For example, a Simple One-Way ANOVA (also called One-Way Independent Groups ANOVA or One way Between Groups ANOVA) would be used to analyze the differences in self-esteem levels (the one continuous variable) across different neighborhoods (the one categorical variable with two or more subcategories, i.e., Sunset, Pacific Heights, and Bay view). The one way ANOVA is an extension of the independent samples *t* test in that it compares averages across two or more subgroups of a categorical variable.ANOVA tables are also used in regression and DOE analyses.Here are the components of an ANOVA table

1. Source - indicates the source of variation, either from the factor, the interaction, or the error. The total is a sum of all the sources
2. DF - degrees of freedom from each source. If a factor has three levels, the degree of freedom is 2 (n-1). If you have a total of 30 observations, the degrees of freedom total is 29 (n - 1).
3. SS - sum of squares between groups (factor) and the sum of squares within groups (error)
4. MS - mean squares are found by dividing the sum of squares by the degrees of freedom.
5. F - Calculate by dividing the factor MS by the error MS; you can compare this ratio against a critical F found in a table or you can use the p-value to determine whether a factor is significant.
6. P - Use to determine whether a factor is significant; typically compare against an alpha value of 0.05. If the p-value is lower than 0.05, then the factor is significant.

2.2 ANOVA TABLES

Suppose you run an ANOVA to determine which of three different colored flyers produced the most sales. You set up the ANOVA so that your factor is "flyer color" which has the three levels of "black and white", "red" and "yellow." Your response variable is weekly sales during the test period, 10 weeks. Since you are examining one factor you use a one-way ANOVA.

Source	DF	SS	MS	F	P
Factor	2	20877338	10438669	136.82	0.000
Error	27	2060002	76296		
Total	29	22937340			

The p-value of 0.000 indicates that the factor of color is significant.

For a two-way ANOVA, you will have two factors and an interaction term. For DOE and regression applications you can have several factors, or sources of variation

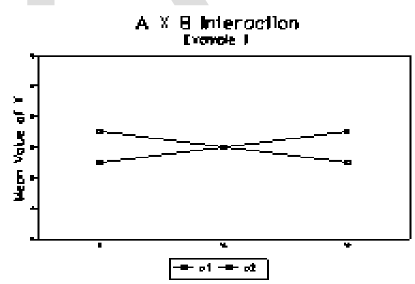
A One-way within Subjects ANOVA (also called Repeated Measures ANOVA) would be used to analyze the differences in one continuous variable across different time periods, phases, or stages of intervention within the same group of participants A two-way ANOVA would be used to analyze the differences in a continuous measure (general health scores) across two characteristics measured categorically (e.g., ethnic group and gender). It is also used to test an interaction effect of the two categorical variables, i.e., whether being female and Latina is related to a particular health level compared to other ethnic and gender groups.

Three factor ANOVA focus on four designs that serve the same function, to test the effects of three factors simultaneously. The designs that will be studied include:

S X A X B X C
S (A) X B X C
S (A X B) X C
A X B X C

Since the naming of the factors is arbitrary, these designs include all possible three factor designs. In a departure from the last few chapters, the similarities of these designs will first be studied.

Each combination of two factors produces a two-way interaction by collapsing over the third factor. The three two-way interactions are interpreted just like the single two-way interaction would be in an A X B design. By collapsing over the C factor, the AB interaction yields the following table and graph. Note that an AB interaction is present because the simple main effect of B does changes over levels of A, in one instance increasing with B and the other decreasing. This table also clearly illustrates the lack of an A or B main effect.



AB Interaction - Example 1

	b_1	b_2	b_3	
a_1	5.5	6	6.5	6
a_2	6.5	6	5.5	6
	6	6	6	6

By collapsing over the B factor, the AC interaction produces the following table and graph. The cells in the table reproduce the numbers which appeared as row means in the full table. In this case there is an AC interaction present.

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	c_1	c_2	
a_1	5	7	6
a_2	7	5	6
	6	6	6

By collapsing over the A factor, the BC table and graph are produced. The numbers in the graph appear as row means on the separate tables in the original data. In this case the interaction is absent.

	b_1	b_2	b_3	
c_1	6	6	6	6
c_2	6	6	6	6
	6	6	6	6

The three-way interaction, ABC, is a change in the simple two-way interaction over levels of the third factor. A simple two-way interaction is a two-way interaction at a single level of a third factor. For example, going back to the original table of means in this example, the simple interaction effect of AB at c_1 would be given in the means in the left-hand boxes. The same simple interaction at c_2 would be given in the right-hand boxes. A change in the simple two-way interaction refers a change in the relationship of the lines. If in both simple two-way interactions the lines were parallel, no matter what the orientation, there would be no three-way interaction. Similarity, if the lines in the simple two-way interactions intersected at the same angle, again no matter what the orientation, there would be no three-way interaction.

2.3 Response Surface Methodology:

In statistics, response surface methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggest using a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but use it because such a model is easy to estimate and apply, even when little is known about the process. Basic approach of response surface methodology: An easy way to estimate a first-degree polynomial model is to use a factorial experiment or a fractional factorial design. This is sufficient to determine which explanatory variables have an impact on the response variable(s) of interest. Once it is suspected that only significant explanatory variables are left, and then a more complicated design, such as a central composite design can be implemented to estimate a second-degree polynomial model, which is still only an approximation at best. However, the second-degree model can be used to optimize (maximize, minimize, or attain a specific target for).

RSM Properties and features: (Response Surface Optimization Using Jmp Software)

Orthogonality: the property that allows individual effects of the k-factors to be estimated independently without (or with minimal) confounding. Also orthogonalty provides minimum variance estimates of the model coefficient so that they are uncorrelated.

Rotatability: The property of rotating points of the design about the center of the factor space. The moments of the distribution of the design points are constant.**Uniformity**: A third property of CCD designs used to control the number of center points is uniform precision (or Uniformity).

Simplex Geometry And Mixture Experiments

Mixture experiments are discussed in many books on the design of experiments, and in the response-surface methodology textbooks of Box and Draper and of Atkinson, Donev and Tobias. An extensive discussion and survey appears in the advanced textbook by John Cornell.

Extensions: Multiple objective functions

Some extensions of response surface methodology deal with the multiple response problem. Multiple response variables create difficulty because what is optimal for one response may not be optimal for other responses. Other extensions are used to reduce variability in a single response while targeting a specific value, or attaining a near maximum or minimum while preventing variability in that response from getting too large.

2.4 Practical Concerns:

Response surface methodology uses statistical models, and therefore practitioners need to be aware that even the best statistical model is an approximation to reality. In practice, both the models and the parameter values are unknown, and subject to uncertainty on top of ignorance. Of course, an estimated optimum point need not be optimum in reality, because of the errors of the estimates and of the inadequacies of the model. Nonetheless, response surface methodology has an effective track-record of helping researchers improve products and services: For example, Box's original response-surface modeling enabled chemical engineers to improve a process that had been stuck at a saddle-point for years. The engineers had not been able to afford to fit a cubic three-level design to estimate a quadratic model, and their biased linear-models estimated the gradient to be zero. Box's design reduced the costs of experimentation so that a quadratic model could be fit, which

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led to a (long-sought) ascent direction.

Vibration measurements are made easy with the PDV-100 Laser Doppler Vibrometer. After focusing the laser beam on the vibrating object the measurement range is set via only two push buttons. An illuminated liquid crystal display shows the selected range, the amount of light returning to the PDV-100, and, if applicable, velocity over-range and low-battery warnings. Selectable high and low pass frequency filters condition the velocity signal to suppress low-frequency background vibrations or unwanted high-frequency signals. The analog velocity output interfaces to conventional analog signal processing and recording equipment. The digital velocity signal uses a transmission method proven in digital audio technology. It interfaces to digital inputs of modern recording devices or signal analyzers without any loss of accuracy. Available accessories include the PDV-BS transportation bag with integrated lithium ion batteries for nominal five hours operation time and VIB-A-TXX series tripods for firm mounting of the PDV-100 during critical measurements. A reliable tool for many applications. If you need a portable multipurpose non-contact vibration measurement system the PDV-100 is the ideal solution. In combination with lightweight signal processing equipment and the PDV-BS transportation bag providing power, machinery vibrations, difficult to access or hazardous objects can conveniently be measured. The PDV-100 is designed for non-contact vibration measurements where mobility and durability are important in Predictive maintenance of machinery, operating vehicles. Multipurpose field testing and scientific expeditions.

3. EXPERIMENTAL PROCEDURE:

In the present study single cylinder four stroke internal combustion engine (petrol) is used to conduct test by varying the different operating conditions viz.., load, speed and compression ratio. Hence in the present experiment the time taken for 10cc fuel consumption has been recorded. Then the analysis is performed by using the Laser Doppler vibrometer, in which a laser beam is focused on the engine where the vibrations obtained have been captured. The time vs displacement graphs were also noted. Fast Fourier transformation was done using a high pass filters within the range of 500 to 10000 and then we got the maximum amplitude of vibration. Design of experiments is made by using the Minitab software. By using the response surface methodology with ANOVA taking speed, load and compression ratios as inputs fault diagnosis of the internal combustion engine based on the fuel consumption and for amplitude was obtained

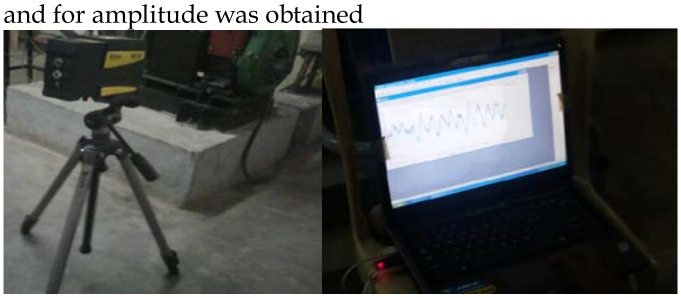

Table1
Observations at speed 2500,2600 rpm

Speed	load	C.R	F Cons	Vibration Amplitude	Speed	Load	C.R	F Cons	Vibration Amplitude
2500	0	4.6	29.03	524.85	2600	0	4.6	31.98	221.93
2500	0	6	27.71	80.52	2600	0	6	28.40	205.21
2500	0	8	29.81	38.42	2600	0	8	30.91	100.05
2500	1	4.6	28.48	498.12	2600	1	4.6	29.88	241.42
2500	1	6	26.92	140.82	2600	1	6	27.31	99.21
2500	1	8	28.32	65.92	2600	1	8	29.04	66.92
2500	2	4.6	26.96	558.65	2600	2	4.6	26.05	252.04
2500	2	6	26.01	86.24	2600	2	6	26.98	101.21
2500	2	8	27.49	41.05	2600	2	8	28.32	70.92
2500	3	4.6	24.42	482.91	2600	3	4.6	25.82	236.42
2500	3	6	25.46	105.12	2600	3	6	26.01	242.39
2500	3	8	26.92	52.15	2600	3	8	27.98	60.00
2500	4	4.6	23.01	501.21	2600	4	4.6	24.16	242.04
2500	4	6	24.39	120.01	2600	4	6	25.29	172.40
2500	4	8	25.03	30.05	2600	4	8	27.36	45.05
2500	5	4.6	23.93	548.65	2600	5	4.6	25.95	269.04
2500	5	6	24.21	94.90	2600	5	6	24.78	220.05
2500	5	8	24.84	23.18	2600	5	8	26.03	32.05

Table2
Observations at speed 2700,2800 rpm

Speed	load	C.R	F Cons	Vibration Amplitude	Speed	Load	C.R	F Cons	Vibration Amplitude
2700	0	4.6	30.09	68.01	2800	0	4.6	35.14	58.91
2700	0	6	28.96	192.10	2800	0	6	35.50	301.92
2700	0	8	31.42	98.52	2800	0	8	33.98	36.82
2700	1	4.6	28.49	89.52	2800	1	4.6	33.52	40.98
2700	1	6	28.05	228.93	2800	1	6	32.59	400.05
2700	1	8	30.80	79.89	2800	1	8	32.46	42.92
2700	2	4.6	27.98	101.03	2800	2	4.6	31.99	53.13
2700	2	6	27.10	242.05	2800	2	6	29.25	335.90
2700	2	8	29.41	42.99	2800	2	8	31.09	50.27
2700	3	4.6	25.78	94.98	2800	3	4.6	27.04	40.47
2700	3	6	27.36	216.30	2800	3	6	28.00	386.25
2700	3	8	28.35	47.54	2800	3	8	30.82	90.82
2700	4	4.6	24.74	79.82	2800	4	4.6	25.60	44.63
2700	4	6	26.86	209.08	2800	4	6	27.41	342.19
2700	4	8	27.24	65.25	2800	4	8	29.00	70.42
2700	5	4.6	23.90	92.98	2800	5	4.6	24.34	39.60
2700	5	6	25.32	219.21	2800	5	6	26.82	333.19
2700	5	8	26.80	50.99	2800	5	8	28.31	105.22

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Table2
Observations at speed 2900,3000 rpm

Speed	load	C.R	F Cons	Vibration Amplitude	Speed	Load	C.R	F Cons	Vibration Amplitude
2900	0	4.6	30.96	58.23	3000	0	4.6	29.68	155.90
2900	0	6	30.03	105.01	3000	0	6	33.88	250.78
2900	0	8	36.49	50.09	3000	0	8	39.00	70.95
2900	1	4.6	28.84	64.30	3000	1	4.6	28.09	140.13
2900	1	6	29.93	149.30	3000	1	6	32.30	236.82
2900	1	8	35.81	63.18	3000	1	8	38.71	114.82
2900	2	4.6	28.30	94.72	3000	2	4.6	26.92	165.82
2900	2	6	29.03	183.93	3000	2	6	31.41	226.05
2900	2	8	34.30	89.42	3000	2	8	37.40	105.92
2900	3	4.6	27.93	66.23	3000	3	4.6	25.85	120.09
2900	3	6	28.31	160.00	3000	3	6	31.98	260.25
2900	3	8	33.98	77.92	3000	3	8	36.39	55.05
2900	4	4.6	26.50	52.01	3000	4	4.6	25.09	153.20
2900	4	6	27.40	186.24	3000	4	6	30.05	192.52
2900	4	8	32.40	56.82	3000	4	8	35.91	85.72
2900	5	4.6	25.97	70.92	3000	5	4.6	24.40	169.91
2900	5	6	26.95	200.05	3000	5	6	30.99	212.89
2900	5	8	31.98	62.18	3000	5	8	34.02	75.05

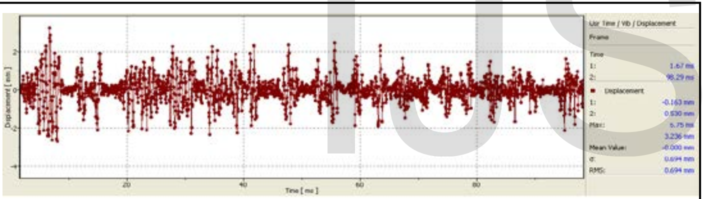

Fig. 1 Time vs. Displacement
At 2500rpm, compression ratio 4.6, load 5kg.

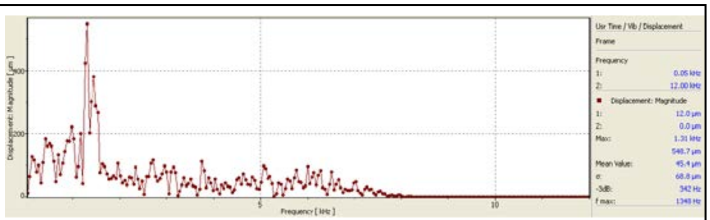

Fig. 2 Vibration amplitude
At 2500rpm ,compression ratio 4.6,load 5kg

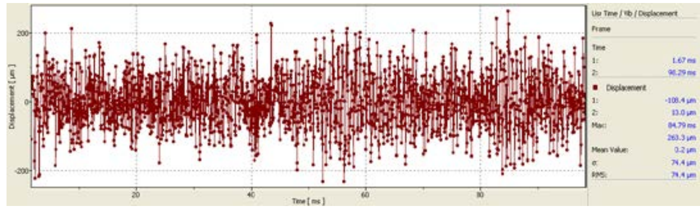

Fig. 3 Time vs. Displacement
At 2500rpm, compression ratio 6, load 5kg.

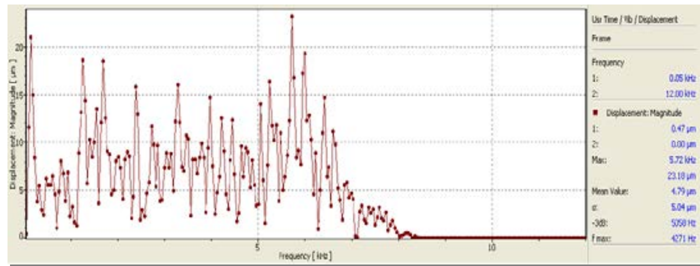

Fig. 4 Vibration amplitude
At 2500rpm, compression ratio 6,load 5kg

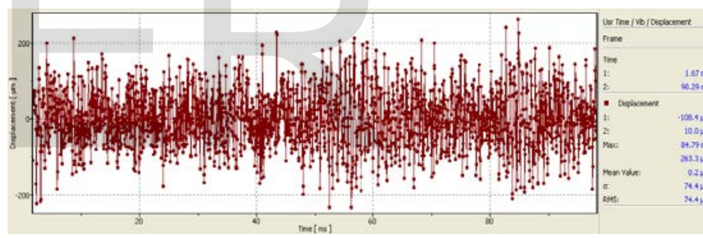

Fig. 5 Time vs. Displacement
At 2500rpm, compression ratio 8, load 5kg

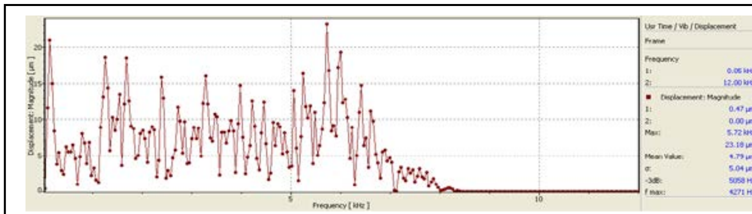

Fig. 6 Vibration amplitude
At 2500rpm ,compression ratio 8,load 5kg

4. RESULTS & DISCUSSIONS

In Analysis of Variance by giving the speed, load, and compression ratios as inputs and then apply the smaller value is better for Fuel consumption analysis.

4.1 Response Surface Regression: F Cons versus Speed, load, C.R

Analysis of Variance for F Cons

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Term	Coef	SE Coef	T	P
Constant	28.2891	0.3116	90.795	0.000 significant
Speed	2.8966	0.1870	15.493	0.000 significant
load	-2.6374	0.1870	-14.107	0.000 significant
C.R	1.8238	0.1560	11.689	0.000 significant
Speed*Speed	0.1342	0.3192	0.421	0.675
load*load	0.5457	0.3192	1.710	0.091
C.R*C.R	0.6287	0.2804	2.242	0.027significant
Speed*load	0.0486	0.2730	0.178	0.859
Speed*C.R	2.1258	0.2272	9.356	0.000significant
load*C.R	0.4319	0.2272	1.901	0.060

S = 1.32391 PRESS = 208.698

R-Sq = 87.20% R-Sq(pred) = 84.45% R-Sq(adj) = 86.02%

4.2 Estimated Regression Coefficients for F Cons using data in uncoded units

Term	Coef
Constant	106.521
Speed	-0.0319328
load	-2.34584
C.R	-15.6775
Speed*Speed	2.14782E-06
load*load	0.0873115
C.R*C.R	0.217548
Speed*load	7.78231E-05
Speed*C.R	0.00500188
load*C.R	0.101632

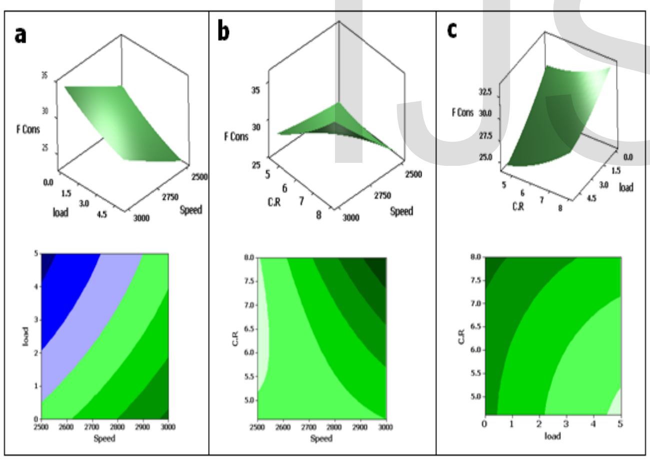


Fig. 7 Response Surface Regression: F Cons versus Speed, load, compression ratio

4.3 Response Surface Regression: Vibration Amplitude versus Speed, load, C.R

In Analysis of Variance by giving the speed, load, and compression ratios as inputs and then apply the smaller value is better for vibration amplitude analysis.

Analysis of Variance for Amplitude

Term	Coef	Coef	T	P	
Constant	173.078	22.02	7.859	0.000	significant
Speed	-29.536	13.21	-2.235	0.028	significant
load	2.295	13.21	0.174	0.862	
C.R	-60.809	11.03	-5.514	0.000	significant
Speed*Speed	57.557	22.56	2.551	0.012	significant
load*load	-3.754	22.56	-0.166	0.868	
C.R*C.R	-73.085	19.82	-3.688	0.000	significant
Speed*load	0.568	19.30	0.029	0.977	
Speed*C.R	85.704	16.06	5.336	0.000	significant
load*C.R	-5.434	16.06	-0.338	0.736	

S = 93.5761 PRESS = 1066621

R-Sq = 88.06% R-Sq(pred) = 85.44% R-Sq(adj) = 93.29%

4.4 Estimated Regression Coefficients for Vibration Amplitude using data in uncoded

Term	Coef
Constant	10157.7
Speed	-6.45586
load	9.47600
C.R	-268.488
Speed*Speed	0.000920911
load*load	-0.600625
C.R*C.R	-25.2888
Speed*load	0.000909388
Speed*C.R	0.201656
load*C.R	-1.27866

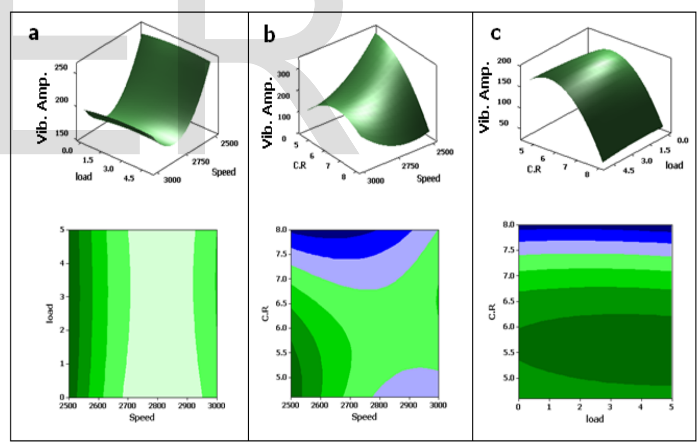


Fig. 8 Response Surface Regression: Amplitude versus Speed, load, compression ratio

4.5 Multi response optimization

Parameters	Goal	Lower	Target	Upper	Weight	Import

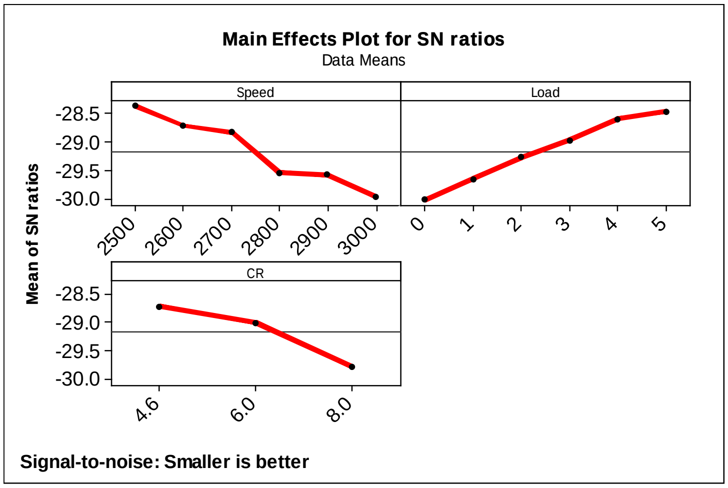
F Cons	Minimum	24	24	39.00	1	1
VibrationAm	Minimum	40	40	558.65	1	1

Starting Point
Speed = 2500
load = 0
C.R = 4.6
Global Solution
Speed = 2500
load = 5
C.R = 7.96566

Predicted Responses

F Cons = 24.1172 desirability = 0.992189
Vibration Am = 39.1048desirability = 1.000000

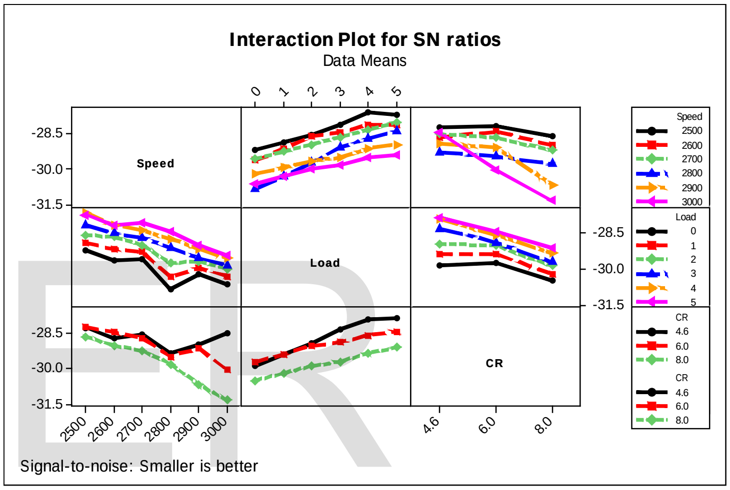
Composite Desirability = 0.996087



Analysis of Variance for SN ratios for FC

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Speed	5	33.987	33.987	6.7974	133.13	0.000
Load	5	32.831	32.831	6.5662	128.60	0.000
CR	2	21.839	21.839	10.9194	213.87	0.000
Speed*Load	25	2.842	2.842	0.1137	2.23	0.008
Speed*CR	10	16.691	16.691	1.6691	32.69	0.000
Load*CR	10	2.314	2.314	0.2314	4.53	0.000
Residual Error	50	2.553	2.553	0.0511		
Total	107	113.056				

S = 0.2260 R-Sq = 97.7% R-Sq(adj) = 95.2%



4.4 Response Table for Signal to Noise Ratios

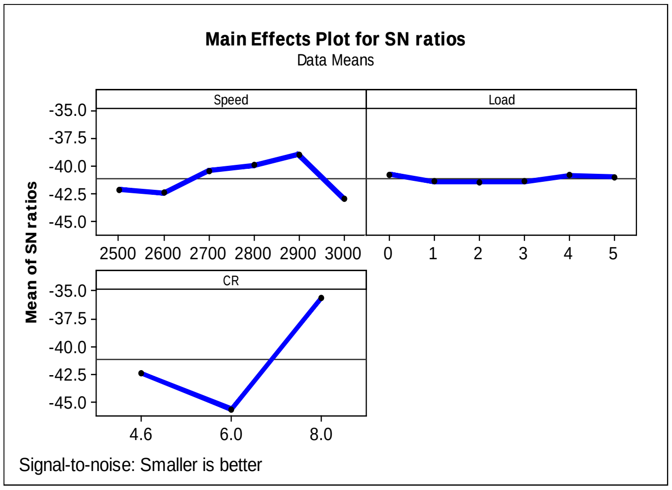
Smaller is better

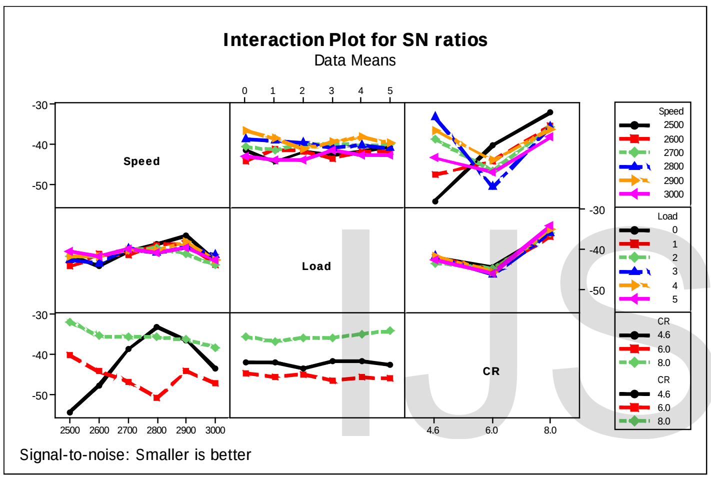
Level	Speed	Load	CR
1	-28.37	-30.02	-28.71
2	-28.71	-29.65	-29.00
3	-28.83	-29.27	-29.78
4	-29.54	-28.97	
5	-29.58	-28.60	
6	-29.96	-28.47	
Delta	1.59	1.55	1.06
Rank	1	2	3

Analysis of Variance for SN ratios for Vibrations

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Speed	5	231.90	231.90	46.381	9.21	0.0
Load	5	8.82	8.82	1.763	0.35	0.880
CR	2	1872.44	1872.44	936.219	185.87	0.0
Speed*Load	25	108.10	108.10	4.324	0.86	0.654
Speed*CR	10	2103.63	2103.63	210.363	41.76	0.000
Load*CR	10	43.61	43.61	4.361	0.87	0.570
Residual Error	50	251.85	251.85	5.037		
Total	107	4620.35				

S = 2.244 R-Sq = 94.5% R-Sq(adj) = 88.3%





4.5 Response Table for Signal to Noise Ratios

Smaller is better

Level	Speed	Load	CR
1	-42.15	-40.80	-42.33
2	-42.46	-41.44	-45.56
3	-40.43	-41.47	-35.57
4	-39.94	-41.39	
5	-38.96	-40.83	
6	-42.99	-41.00	
Delta	4.03	0.66	9.99
Rank	2	3	1

5. Conclusions

An investigation of the fault diagnosis technique in internal combustion engines based on the fuel consumption and vibration signals is done. Experiments are carried out to evaluate the proposed system for fault diagnosis under various fault conditions.

1. Based on the Response surface methodology anova shows that the individual factors are significant while the interactions are not significant.
2. Fuel consumption increases with load and compression ratio
3. Vibration increases with load and decreases with compression ratio.
4. The optimal combination of fuel combustion and vibration is at speed 2500rpm, load 5kg, C.R 7.96
5. Fuel consumption is better at 24.1172sec, and vibration amplitude at 39.1048μm.
6. The ranking of parameters for fuel consumption is speed 1, load 2, compression ratio 3
7. The ranking of parameters for vibration is compression ratio 1, speed 2, load 3
8. Based on the anova of vibration speed and compression ratio and their interactions are only significant.

The experimental results indicate that the proposed technique is effective in the fault diagnosis of an internal combustion engine.

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