Experimental Investigation for Fault Diagnosis of a Single Stage Worm Gearbox Using Response Surface Methodology

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ABSTRACT: Gearbox transmission system is a fundamental factor in the industrial applications. If gearbox stop working due to different faults, it may break normal machine operation and cause a production loss. This research paper focused on fault analysis of combination of worm wheel and bearing by using root mean square (RMS) and response surface method (RSM). Faults considered on outer race and inner race of worm wheel bearing, on worm wheel tooth. These faults and load were considered as an important independent factor to understand their effects on RMS response of worm gearbox. Worm gearbox experimental setup is for laboratory experimentation and RSM for analysis. Twenty-seven experimental trial conducted for three level of parameters based on design of experiment (DOE). Vibration based response measured in frequency domain and root mean square parameter extracted for the fault analysis. Box behnken design RSM is implemented to investigate independent parameters effect on output parameter i.e. RMS. The result shows that effect of faulty inner race bearing is more on worm wheel as compared to faulty outer race bearing and fault parameter influence RMS than load parameter.

KEYWORDS: Design of experiment, Production loss, Response Surface Method, Worm wheel Bearing, Worm wheel.

[Received Jul. 27, 2022; Revised Oct. 31, 2022; Accepted Nov. 6, 2022] Print ISSN: 0189-9546 | Online ISSN: 2437-2110

I. INTRODUCTION

Fault analysis in intricate engineering systems depends on data acquisition through experiments, signal processing methods to analyse the data for feature extraction and mapping the extracted features to assess the state of the machine. (Patil *et al*, 2023) evaluate the effect of load, rotor defect, and speed on vibration based RMS response by using noncontact type of sensor and response surface methodology (RSM). Result shows that rotor speed and rotor defect seriousness influence RMS response more than load. For reliability determination and efficiency of machine and machine components, appropriate fault analysis of machine and machine components by using vibration monitoring is crucial (Ammar *et al*, 2022). Experiment data analysis provides valid research and provides useful relevance. It is necessary to make use of correct experimental setup and statistical method to improve experiment data analysis. Condition monitoring of gearbox of all automobiles, conveyors, escalators, press, mining, rolling mills, blending machine, machine tools, aircraft, turbines etc. are important because most of the time gear boxes fail due to fault present in gears or bearings (Dhamande and Chaudhari, 2018). In industrial applications such as conveyors, escalators, press, mining, rolling mills, blending etc. worm gearboxes are key element. In the case of the worm gearbox, as the material of the worm wheel is softer than that of the worm screw, the worm wheel gear is vulnerable to failure through various modes like pitting, wearing out, or tooth breakage during the sliding process (Waqar and Demetgul, 2016). In fault analysis, vibration signatures are measured by using data acquisition and sensors. Extracted vibration signals are analysed in the time domain, frequency domain, time-frequency domain (Attoui *et al*, 2017). Statistical feature parameters such as mean, median, RMS, standard deviation, peak-to-peak, kurtosis, crest factor are used for vibration signal analysis. In past research, RMS is plays vital role to analyse the relationship between faults and vibration amplitude (Umutlu *et al*, 2020). In the literature, experimental investigations were observed using DOE and vibration responses are analysed by RSM for fault detection in bearing (Mishra and Jalan, 2021). The design of experiments methods such as factorial design, response surface method (RSM), Placket-Burmann design (PBD) and Taguchi techniques was used (Jankovic *et al*, 2021). To extract vibration signal accurate sensor mounting plays a vital role in fault diagnosis of the rotating machine. RSM effectively examine statistical parameter i.e RMS for sensor placement on a rotating machine (Vanraj *et al*, 2017; Goyal *et al*, 2019). (Ahmad *et al*, 2020) analysed ultrasound-assisted extraction health by Box–Behnken RSM and the study of its antioxidant potential. The result shows that RSM statistical model with the experimental data is reliable, adequate, and precise. Three-level full factorial design (Box–Behnken design) and central composite design (CCD) in concurrence with RSM has effectively used for fault analysis of rotor-bearing system and leaching process (Ahmad *et al*, 2020; Patil *et al*, 2010; Behera *et al*, 2018). (Slimane *et al*, 2018) applied RSM to analysed

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doi: http://dx.doi.org/10.4314/njtd.v18i4.1259

vibration amplitude, tool rotation speed and feed rate parameter's effect on cutting force on the drilling of carbon fiber reinforced plastic composites. (Kankar *et al*, 2011; 2009), investigate localized defects in high-speed rolling bearings by DOE and RSM.

In the present work, RSM is used for fault analysis of the worm wheel and bearing combination of a single stage worm gearbox. Different dimensions faults were created artificially on the worm wheel bearing outer race and inner race and on the worm wheel tooth by using a wire cutting machine and file tool respectively. DOE was used to design experiments trials. Vibration signatures were measured for different fault conditions by using an FFT analyser and RMS parameter was extracted for RSM analysis.

Aim of the current research paper is to investigate the effect of fault present on worm wheel and bearing on vibration signature based root mean square (RMS) wherein RSM is used for the investigation.

II. METHODOLOGY

A. *Design of Experiment*

(DOE) is a statistical analysis applied for building and performing research experiments as well as analysing and validating data obtained from the research experiments (Durakovic, 2017). DOE is a branch of applied statistics that is applied for performing research studies of a system, process, or product in which independent parameters were applied to investigate its consequence on measured dependant parameters (Barad, 2014).

B. *Response Surface Methodology*

RSM is a group of mathematical and statistical techniques useful for the modelling and analysis of experimental data, affected by various independent parameters. RSM is effectively used for design, formulation, development, and optimization. RSM is utilized in various industrial applications such as chemical process, sheet metal process and metal joining, structural damage, statistical modification analysis of helical gear and cutting (Karimifard and Moghaddam, 2018; Mukhopadhyay *et al*, 2015; Jun and Fan, 2015). To decrease the cost and time of analysis of experimental data, different types of RSM methods are available like central composite design, Box-Behnken design, one-factor design, 3-level factorial design, and optimal design.

A linear model of RSM shows the relation between an independent factor and output factor as, (Montgomery, 2017).

$$Y = a_0 + \sum_{i=1}^{n} a_i\, x_i \qquad (1)$$

A second-order model of RSM used to the overcome drawback of a linear model of RSM

$$Y = a_0 + \sum_{i=1}^{n} a_i\, x_i + \sum_{i=1}^{n} a_i\, {x_i}^2 + \sum_{i=1}^{n}\sum_{J=1}^{n} a_{ij}\, x_{ij} \qquad (2)$$

Where xi and xj are the design variables or independent variables and y is the dependent or output parameter, is the polynomial regression coefficient, and k is the number of factors.

C. *Methodology*

The methodology followed in this research consists of the following steps:

1) It consists of manufacturing of an experimental setup and artificial faults created in worm wheel bearing inner race and outer race and worm wheel teeth.
2) Four independent parameters namely faulty worm wheel bearing outer race, faulty worm wheel bearing inner race, faulty worm wheel and load considered with three levels.
3) Box-behnken design (RSM) method is used to perform DOE for designing experiments trials.
4) Vibration signatures are measured with RMS parameters by using an FFT analyser for twenty-seven experiments trials.
5) Analysis of variance (ANVOA) performed for measured vibration signature with RMS parameters.

Different RSM plots like Surface plots, main effect plots and combine effect plots were drawn to analyse the effect of independent parameters on RMS parameters. Finally, validation of the RSM Model with experimental data was investigated.

III. DATA COLLECTION

A. *Vibration Signature Measurement by OR34 FFT Analyser*

In this research as shown in Figure 1 experimental test rig has been fabricated to conduct trials under constant rotational speed of 2880 r.p.m. provided by three-phase AC motor 0.75 kW 2880 rpm, 1/15 gear ratio worm gearbox. Single stage worm gearbox consists of the worm of double threaded made of case-hardened steel and profile ground and the worm wheel has 30 teeth made of shell-cast ZCuSn12 bronze. The speed of the gearbox is controlled by a variable frequency drive. Rope brake dynamometer is used to apply load on the gearbox. The load varies from 10 kg to 20 kg. As mentioned in Table 2 twenty-seven different dimensions of artificial faults on the bearing inner race, bearing outer race and worm wheel teeth are created by using a wire cutting machine, grinder machine and file tool. Sample of artificial faults is shown in Figure 3.

To use vibration signature effectively and efficiently to monitor the condition of the worm gearbox, characteristics rotational frequencies are calculated for the respective load and speeds. Then raw vibration signatures are extracted in the frequency domain by using a uniaxial accelerometer having a sensitivity of 100 mv/g mounted in the radial direction as shown in Figure 2 and four channel OR 34 FFT analyser. The vibration signature amplitude change is negligible when the accelerometer is mounted in an axial direction as compared to the accelerometer mounted in a radial direction. Thus accelerometer is mounted in a radial direction. In signal processing, denoising is a method that is used to reconstruct a vibration signal from a contaminated signal. It aims is to remove noise and preserve useful information. In condition monitoring of rotating machinery, extracted vibration signatures from the accelerometer sensors are contaminated by background noise, electromagnetic interference, vibration originating from other components of the machine such as motor, the data acquisition system. Therefore, the initial task of fault analysis is separate the actual mechanical vibration signal from the contaminated signal. In this experiment contaminated vibration signatures are denoised by using NV Gate software.

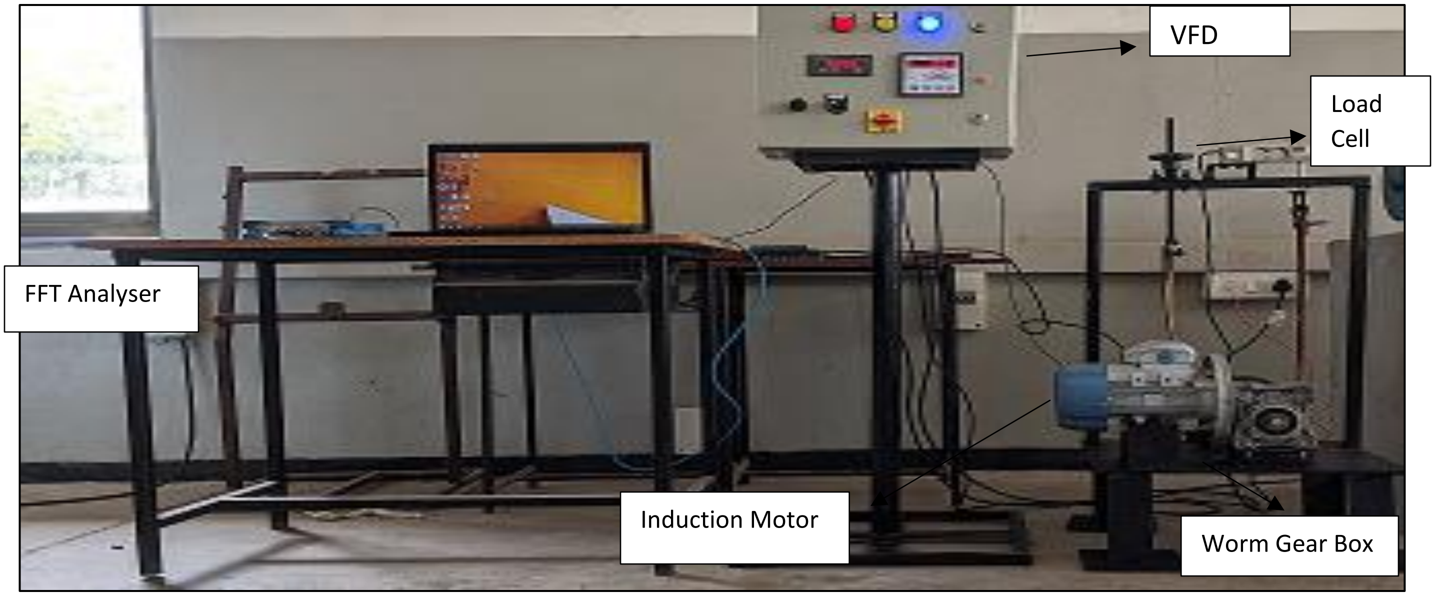


Figure 1: Worm gearbox experimental setup

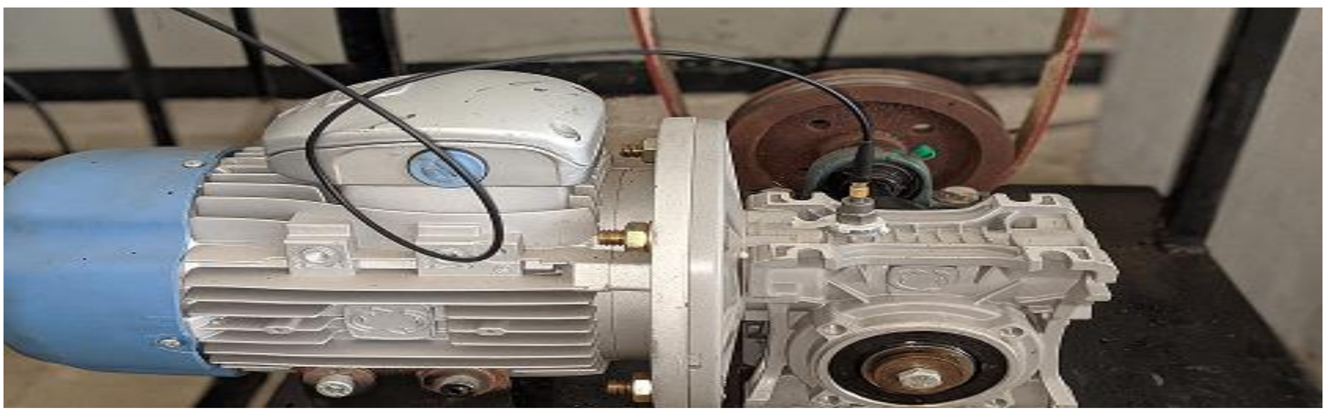


Figure 2: Mounting of accelerometer

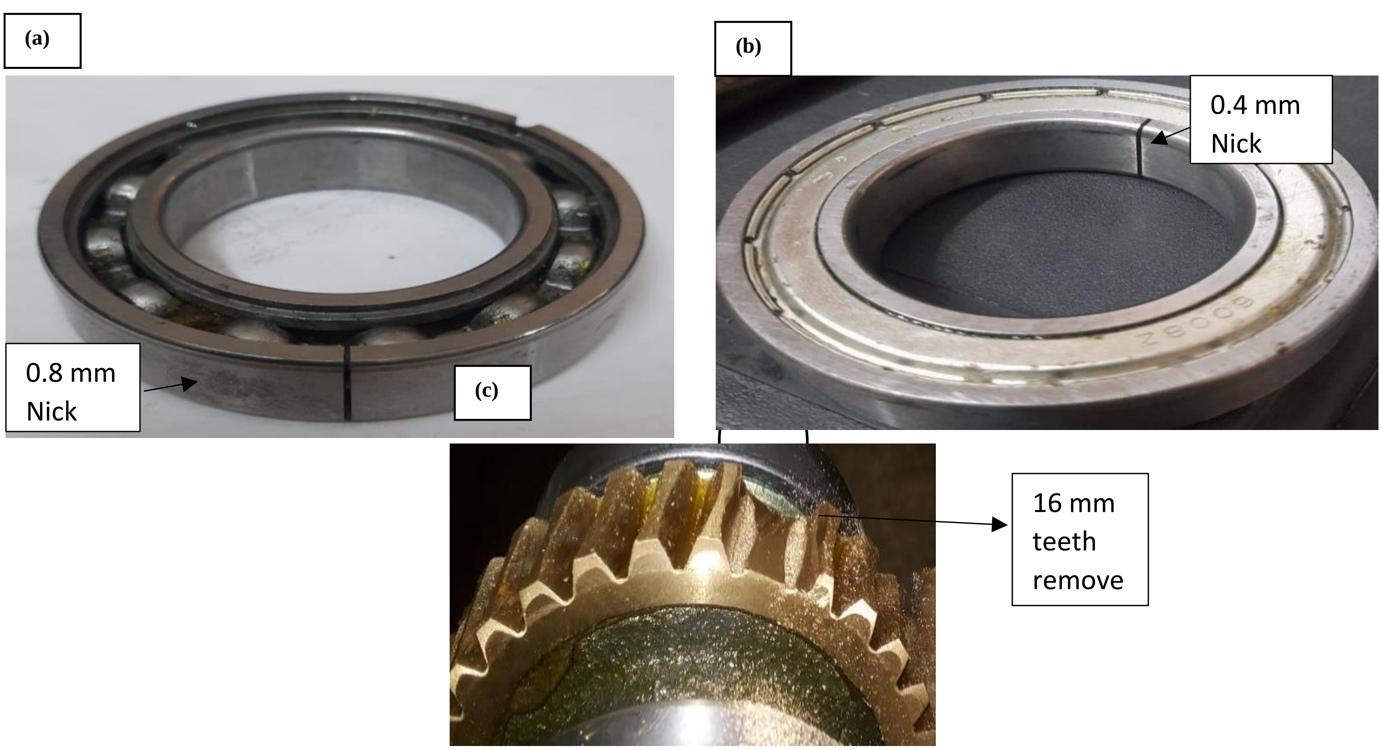


Figure 3: Sample images of artificial faults on : (a) bearing outer race (b) bearing inner race (c) worm wheel teeth

B. Design of Experiment

In this research DOE based on Box-behnken design RSM method is used to design experimental trials for three levels with four factors as shown in Table 1. Experimental trials were performed to measures vibration signatures with RMS response. Table 2 represent twenty-seven experimental trials matrix and RMS response value measured in vertical direction.

Table 1: Parameters with their levels

Symbols for independent parameters	Independent parameters	Minimum level	Middle level	Maximum level
IR	Fault on bearing inner race	0	0.4 mm	0.8 mm
OR	Fault on bearing outer race	0	0.4 mm	0.8 mm
WW	Fault on worm wheel teeth	0	8 mm	16 mm
LOAD	Load applied	10 kg	15 kg	20 kg

than faulty bearing inner race, faulty bearing outer race, or load. From the ANOVA table; models having P-values less than 0.05 are significant models. Therefore, IR, OR, WW, LOAD, IR^2, OR^2, WW^2, IR×OR, IR×WW, WW×LOAD models are significant. On the other hand, models $LOAD^2$, IR×LOAD, OR×WW, OR×LOAD whose P- value is greater than 0.05; these models are non-significant. Eqn. 3 represents a second-order regression equation in uncoded units. The relationship between parameter coefficients can be determined by regression equation in uncoded units.

$$\begin{aligned} \mathrm{RMS} = \; & 0.4269 + 0.0578\,\mathrm{IR} + 0.0556\,\mathrm{OR} \\ & + 0.02648\,\mathrm{WW} + 0.00248\,\mathrm{LOAD} \\ & - 0.0822\,\mathrm{IR}^2 - 0.1105\,\mathrm{OR}^2 - 0.000956\,\mathrm{WW}^2 \\ & - 0.000005\,\mathrm{LOAD}^2 + 0.1131\,\mathrm{IR}\times\mathrm{OR} \\ & + 0.003903\,\mathrm{IR}\times\mathrm{WW} + 0.00121\,\mathrm{IR}\times\mathrm{LOAD} \\ & + 0.000391\,\mathrm{OR}\times\mathrm{WW} + 0.00196\,\mathrm{OR}\times\mathrm{LOAD} \\ & - 0.000227\,\mathrm{WW}\times\mathrm{LOAD} \end{aligned} \tag{3}$$

Table 2: Experimental matrix with measured responses

Standard order	Experiment run order	Fault type	IR (mm)	OR (mm)	WW (mm)	LOAD (kg)	RMS (mm/s)
1	12	FT1	0	0.4	0	15	0.48
2	17	FT2	0.4	0	0	15	0.48
3	27	FT3	0	0	8	15	0.59
4	2	FT4	0.4	0.4	0	10	0.50
5	18	FT4	0.4	0.4	0	20	0.53
6	9	FT5	0.4	0.8	0	15	0.51
7	4	FT6	0.8	0.4	0	15	0.52
8	13	FT7	0	0.4	8	10	0.59
9	23	FT7	0	0.4	8	20	0.61
10	19	FT8	0	0.4	16	15	0.61
11	11	FT9	0	0.8	8	15	0.59
12	6	FT10	0.4	0	8	10	0.61
13	10	FT10	0.4	0	8	20	0.62
14	20	FT11	0.4	0	16	15	0.63
15	3	FT12	0.8	0	8	15	0.62
16	24	FT13	0.4	0.4	16	10	0.67
17	7	FT13	0.4	0.4	16	20	0.66
18	8	FT14	0.4	0.8	8	10	0.64
19	5	FT14	0.4	0.8	8	20	0.67
20	21	FT15	0.4	0.4	8	15	0.65
21	22	FT15	0.4	0.4	8	15	0.65
22	25	FT15	0.4	0.4	8	15	0.65
23	16	FT16	0.4	0.8	16	15	0.67
24	14	FT17	0.8	0.4	8	10	0.66
25	1	FT17	0.8	0.4	8	20	0.69
26	15	FT18	0.8	0.4	16	15	0.70
27	26	FT19	0.8	0.8	8	15	0.69

IV. RESULTS AND DISCUSSION

A. ANOVA for RMS Response

Minitab 18 tool has applied for RMS-based fault analysis of worm gearbox. The mean square (MS) and sum square (SS) of second-order polynomials were calculated, and ANOVA was applied to examine the significance of polynomials by testing “prob>F” which is less than 0.05 with 95% CI (confidence interval) at 5% level of significance. Table 3 shows that ANOVA for vertically calculated RMS. It is observed that WW (worm wheel) F- value is 2084.17 greater than (IR) bearing inner race value 433.18, (OR) bearing outer race value 117.19 and load 28.43. Thus fault on the worm wheel individually or in combination with faulty bearing inner race or faulty bearing outer race influence RMS response more

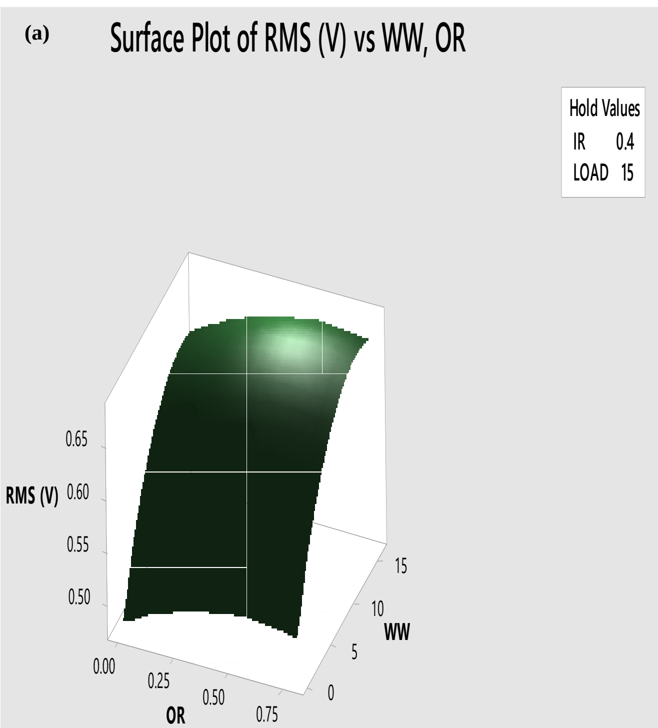
B. RSM 3D Surface Plot

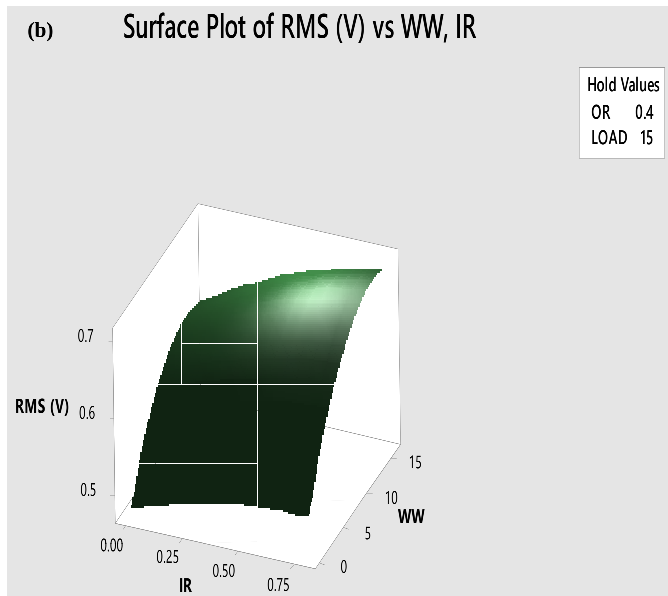
The graphical representation technique, known as a RSM 3D surface plot is fruitful to study the effect of independent parameters on dependent parameters. To analysed RMS Vs WW, RMS Vs IR, RMS Vs OR and RMS Vs Load; a 3D surface plot is shown in Figure 4. Figure 4 (a) and 4 (b) analyses the effect of different dimensions’ faults in the worm wheel, bearing outer race and bearing inner race on vibration signature base RMS response for load varying from 10 kg to 20 kg. RMS response increases with the increase in fault dimensions. When fault in the worm wheel; RMS response is influenced more as compared to a fault in the bearing outer race and bearing inner race. Also the combination of faults in worm wheel and bearing inner race shows greater RMS response than

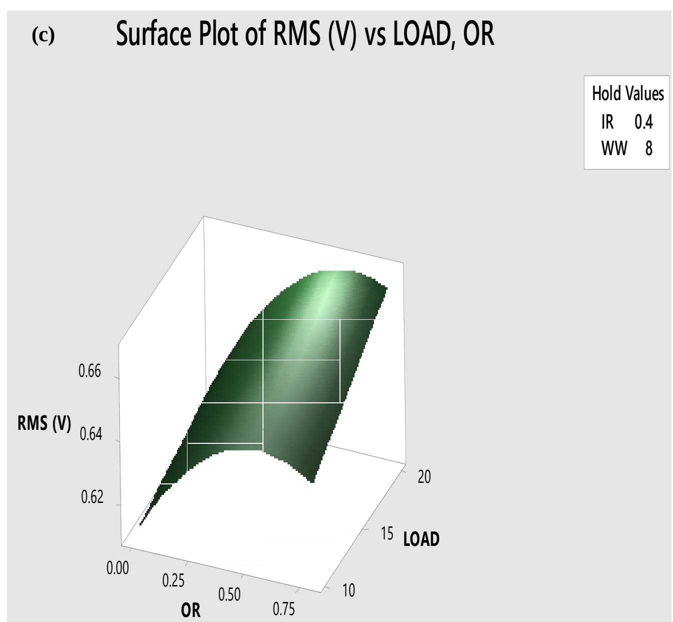
Table 3: ANOVA for RMS response

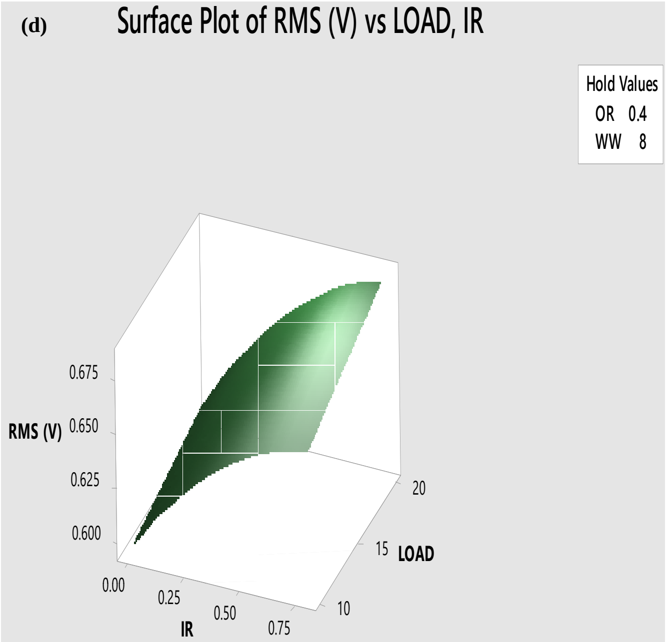
Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-value	P-value
Model	14	0.113286	99.65%	0.113286	0.008092	243.71	0.000
Linear	4	0.088418	77.77%	0.088418	0.022104	665.74	0.000
IR	1	0.014383	12.65%	0.014383	0.014383	433.18	0.000
OR	1	0.003891	3.42%	0.003891	0.003891	117.19	0.000
WW	1	0.069200	60.87%	0.069200	0.069200	2084.17	0.000
LOAD	1	0.000944	0.83%	0.000944	0.000944	28.43	0.000
Square	4	0.022514	19.80%	0.022514	0.005628	169.52	0.000
IR^2	1	0.000047	0.04%	0.000923	0.000923	27.81	0.000
OR^2	1	0.000035	0.03%	0.001667	0.001667	50.20	0.000
WW^2	1	0.022432	19.73%	0.019968	0.019968	601.40	0.000
$LOAD^2$	1	0.000000	0.00%	0.000000	0.000000	0.00	0.959
2-Way Interaction	6	0.002354	2.07%	0.002354	0.000392	11.82	0.000
IR×OR	1	0.001309	1.15%	0.001309	0.001309	39.42	0.000
IR×WW	1	0.000624	0.55%	0.000624	0.000624	18.79	0.001
IR×LOAD	1	0.000023	0.02%	0.000023	0.000023	0.70	0.419
OR×WW	1	0.000006	0.01%	0.000006	0.000006	0.19	0.672
OR×LOAD	1	0.000062	0.05%	0.000062	0.000062	1.85	0.198
WW×LOAD	1	0.000330	0.29%	0.000330	0.000330	9.94	0.008
Error	12	0.000398	0.35%	0.000398	0.000033		
Lack-of-Fit	10	0.000382	0.34%	0.000382	0.000038	4.58	0.192
Pure Error	2	0.000017	0.01%	0.000017	0.000008		
Total	26	0.113684	100.00%				

combination of fault in the worm wheel and the bearing outer race. From the surface plot as shown in Figures 4 (c), 4 (d) and 4 (e); to study the influence of fault in bearing outer race, bearing inner race, worm wheel and load on vibration-based RMS response. Load influence on RMS response is less as compared to different dimensions' combination faults.









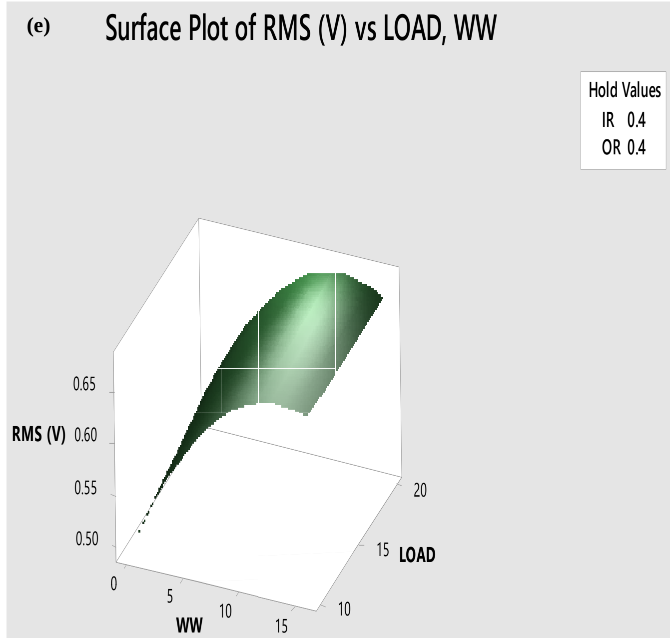


Figure 4: RSM surface plot

V. VALIDATION of RMS RESULT THROUGH EXPERIMENTATION and RSM ANALYSIS

From a validation point of view random faults combination of worm wheel, bearing inner race and bearing outer race was considered for loads 10 kg and 20 kg. Vibration-based RMS response value is calculated through experimentation and RSM analysis by using regression equation in uncoded units as mentioned in Equation 3. Table 6 shows actual RMS and predicted RMS values with a percentage error below six percent. From the validation main effect plot as shown in Figure 5; though the fault combination changes; the trend of RMS value change is the same i.e fault dimensions change RMS value increases. The same trend of RMS Value change was obtained through experimentation.

As shown in Figure 5; the red colour dimension shows the actual experimental dimension. Dimensions varied between low to high. The main effect plot inclination curve indicated that the RMS value increases when fault size increases and load increases. But load influence on RMS responses was less as compared to different dimension faults.

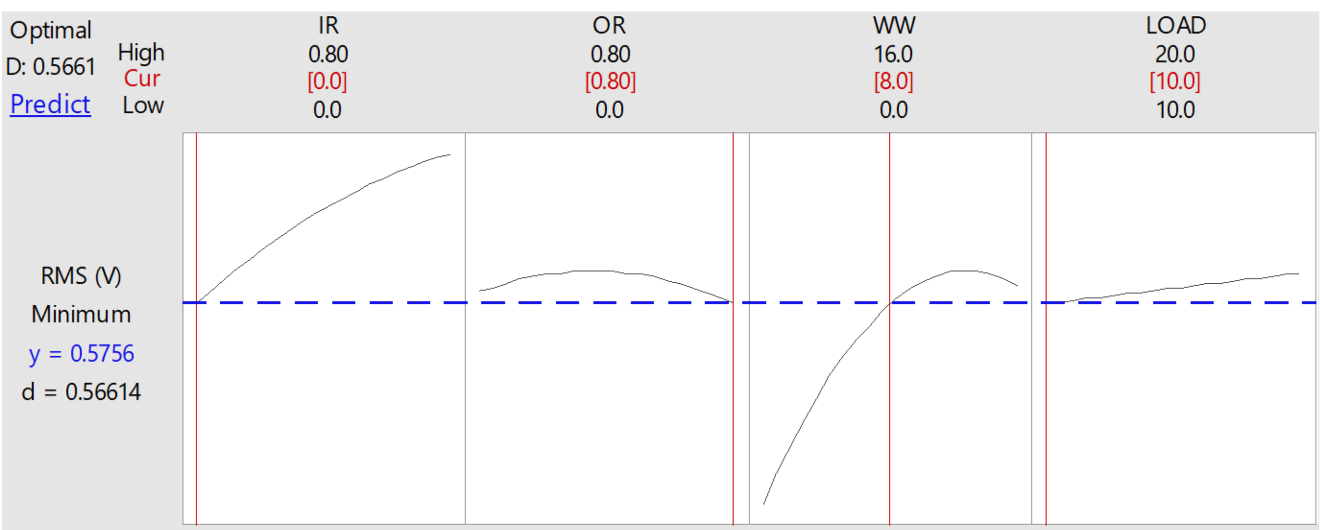
Sample calculation of percentage error =

$$\frac{\textbf{Actual RMS} - \textbf{Predicted RMS}}{\textbf{Predicted RMS}} \times 100 \quad (4)$$

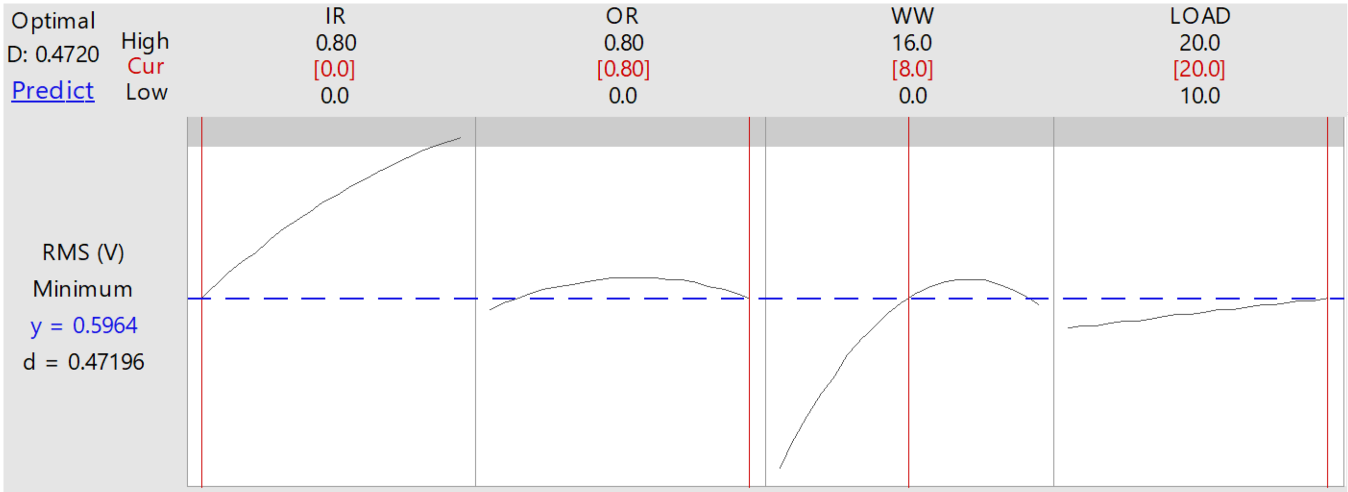
Percentage error =

$$\frac{0.607258 - 0.5756}{0.5756} \times 100$$

Percentage error = 5.5%



(a)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Predict
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Cur
Low
IR
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OR
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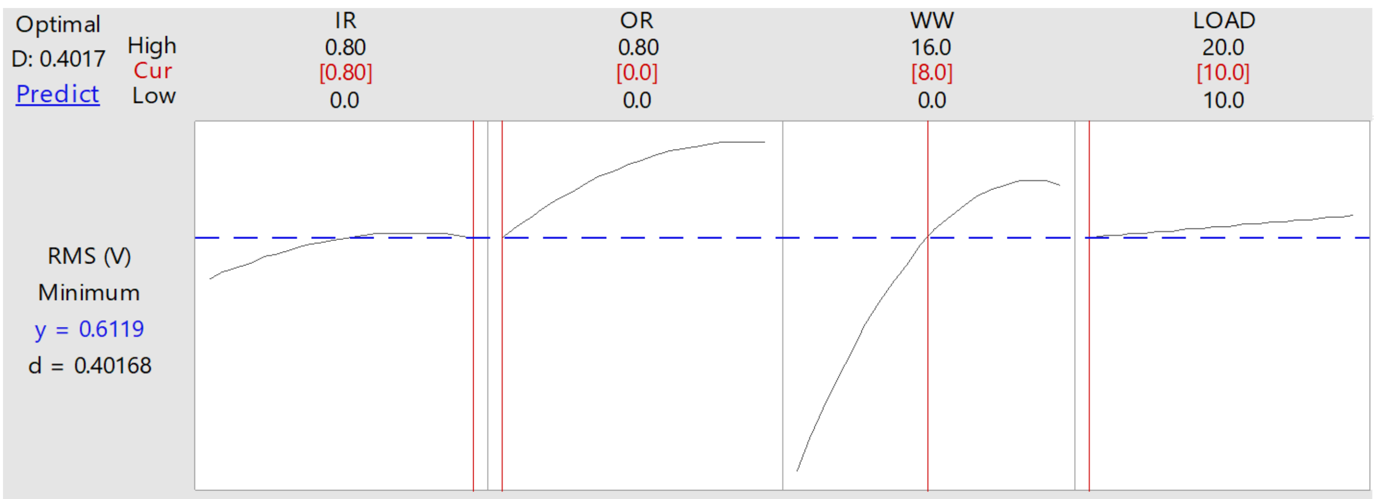
0.0
WW
16.0
[8.0]
0.0
LOAD
20.0
[20.0]
10.0
RMS (V)
Minimum
y = 0.5964
d = 0.47196

(b)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WW
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LOAD
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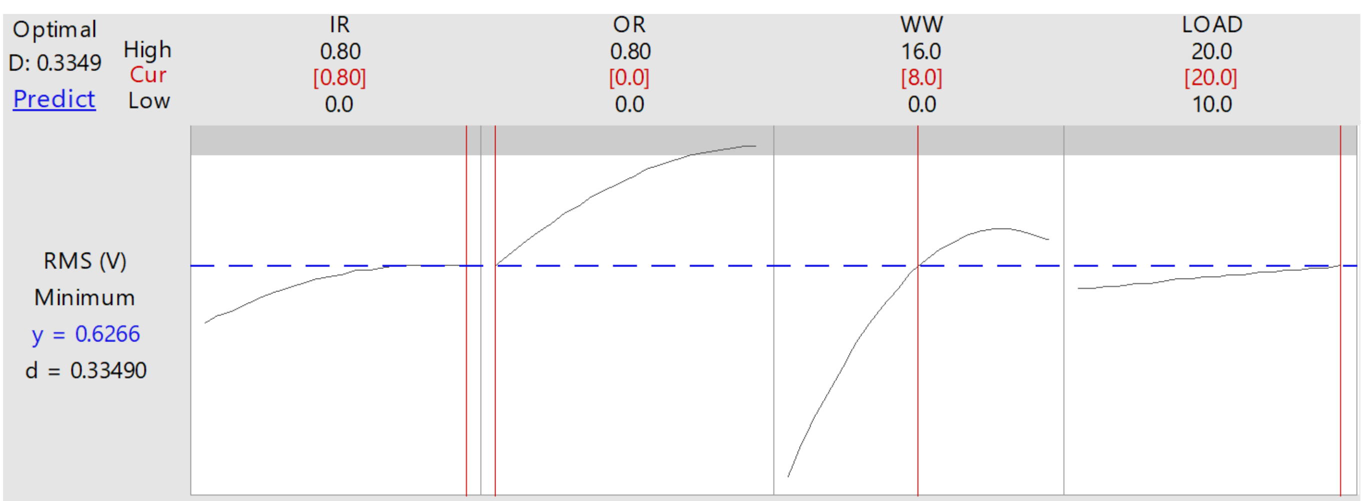
10.0
RMS (V)
Minimum
y = 0.6119
d = 0.40168

(c)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0.0
WW
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LOAD
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10.0
RMS (V)
Minimum
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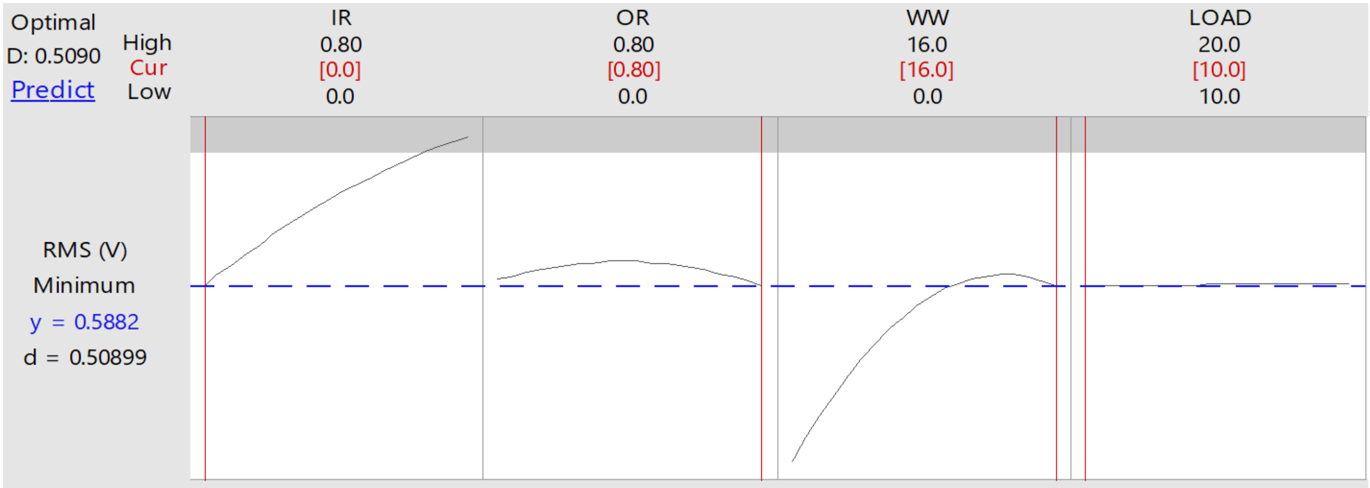
d = 0.33490

(d)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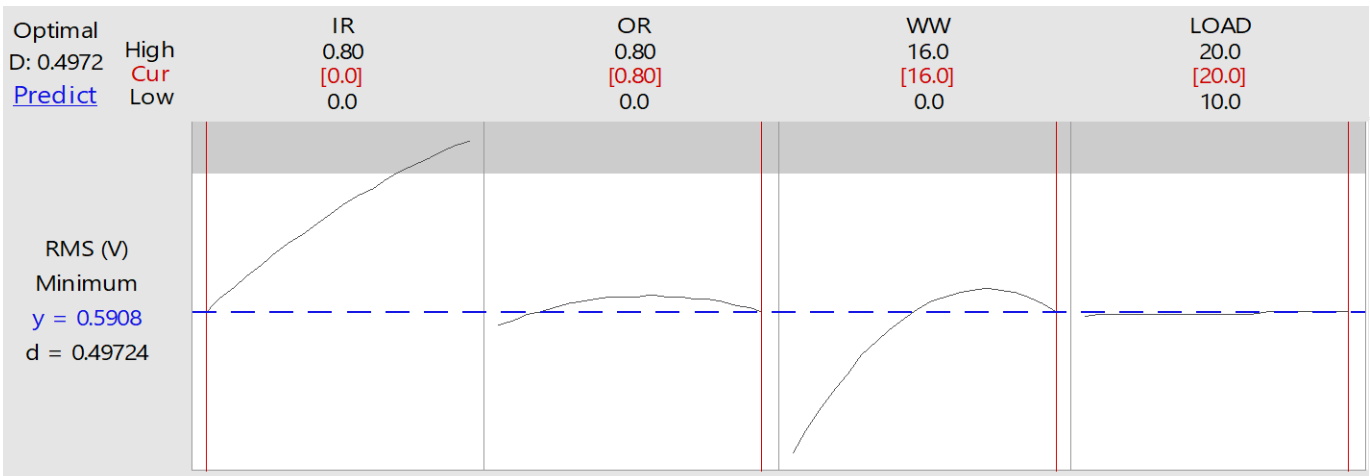
d = 0.50899

(e)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0.0
LOAD
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Minimum
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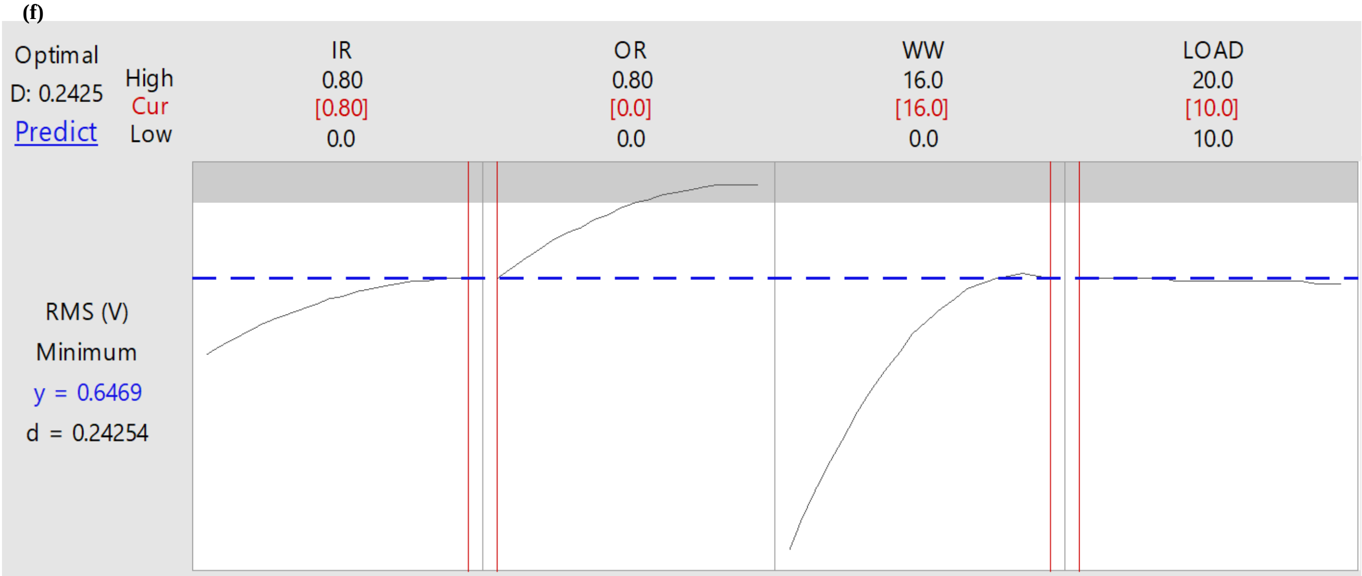
d = 0.49724

(f)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WW
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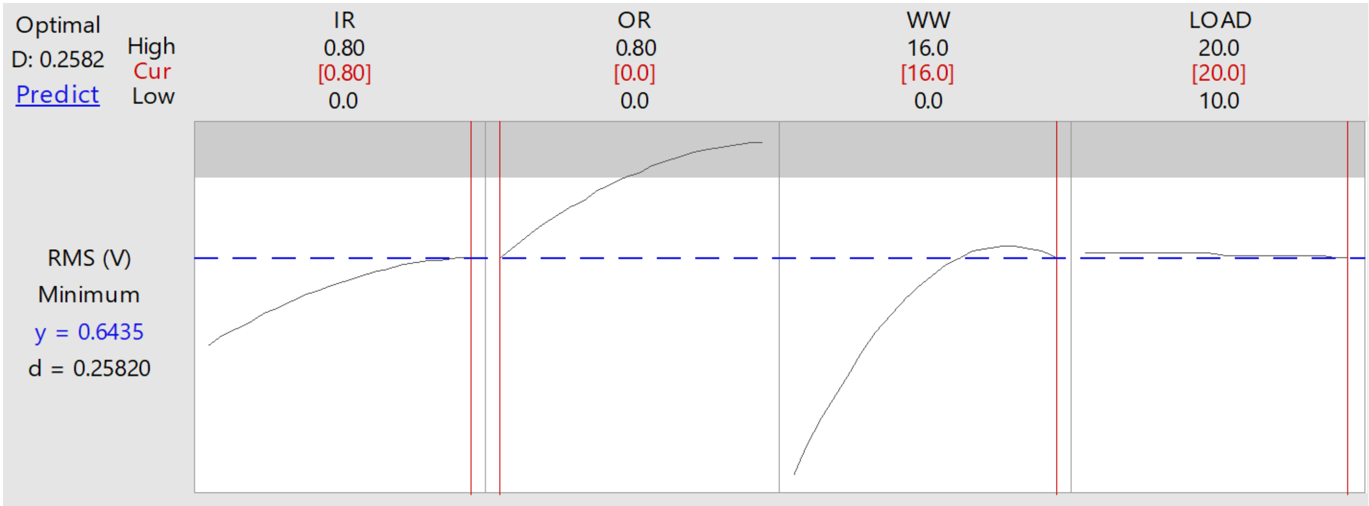
d = 0.24254

(g)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LOAD 20.0 [20.0] 10.0
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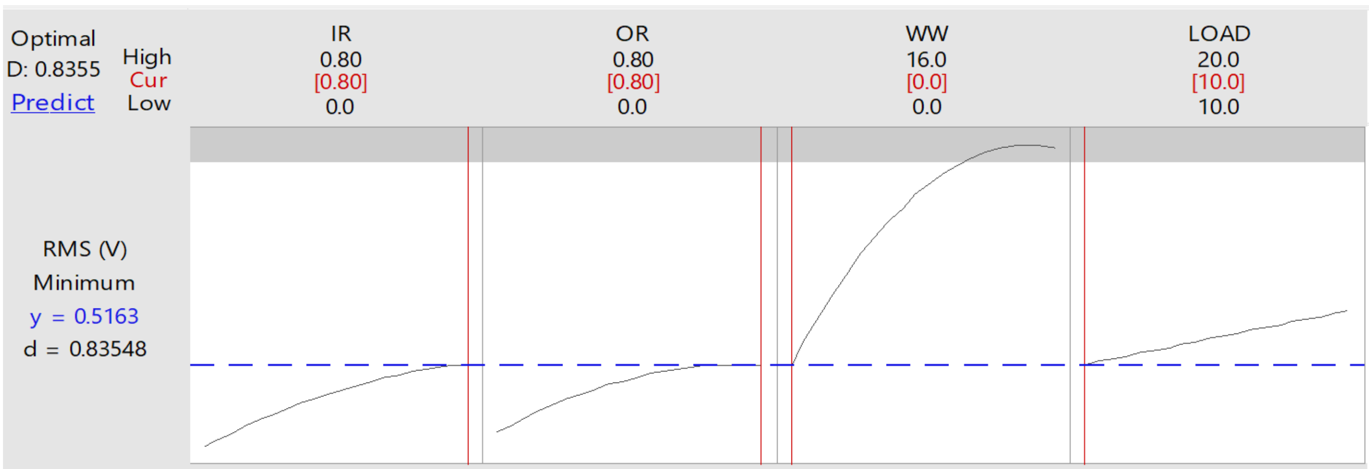
d = 0.25820

(h)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RMS (V)
Minimum
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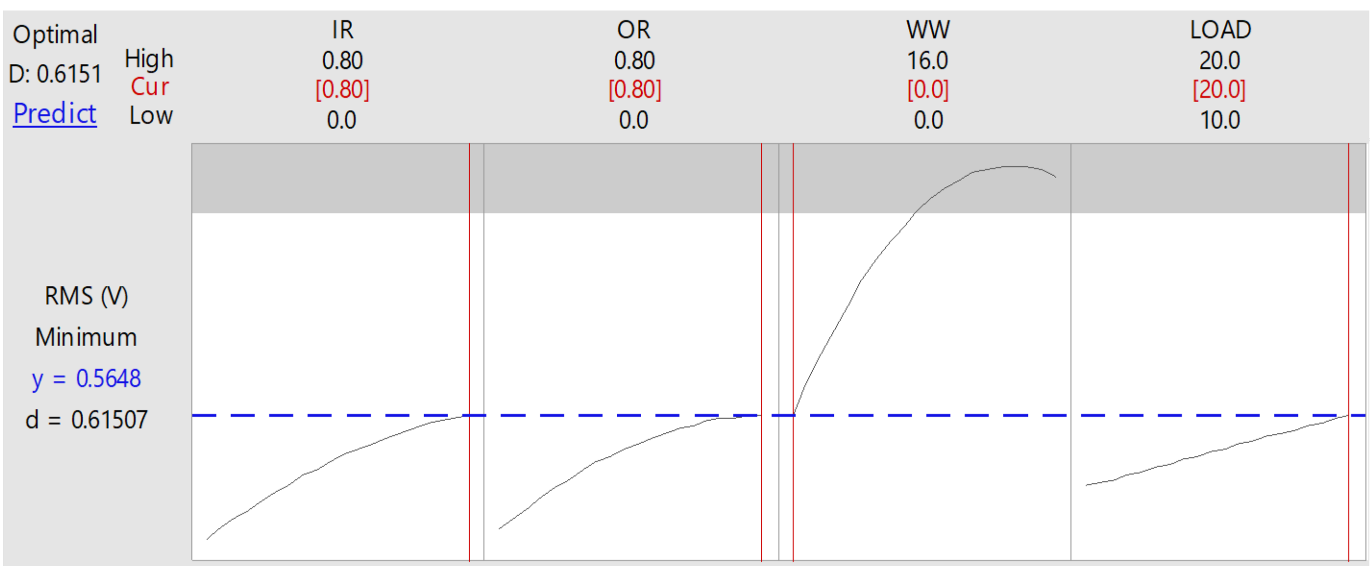
d = 0.83548

(i)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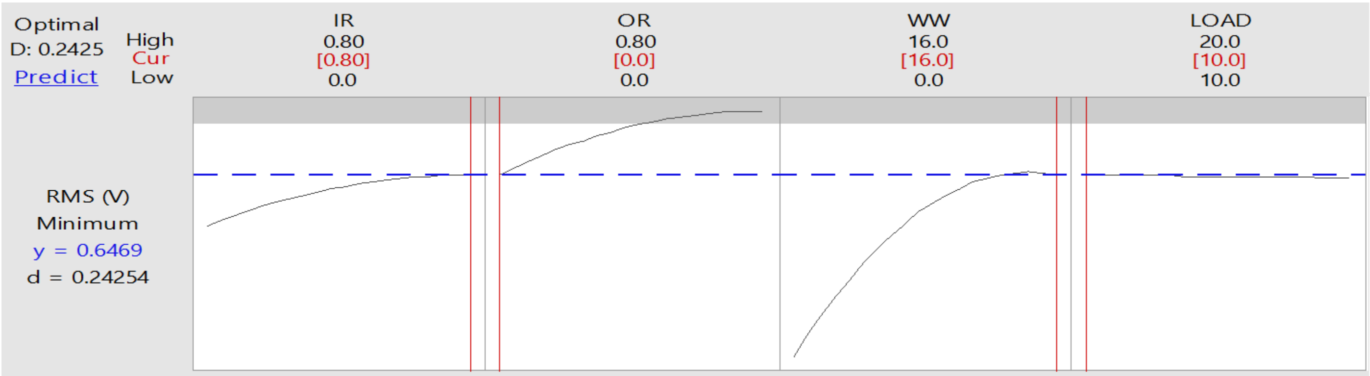
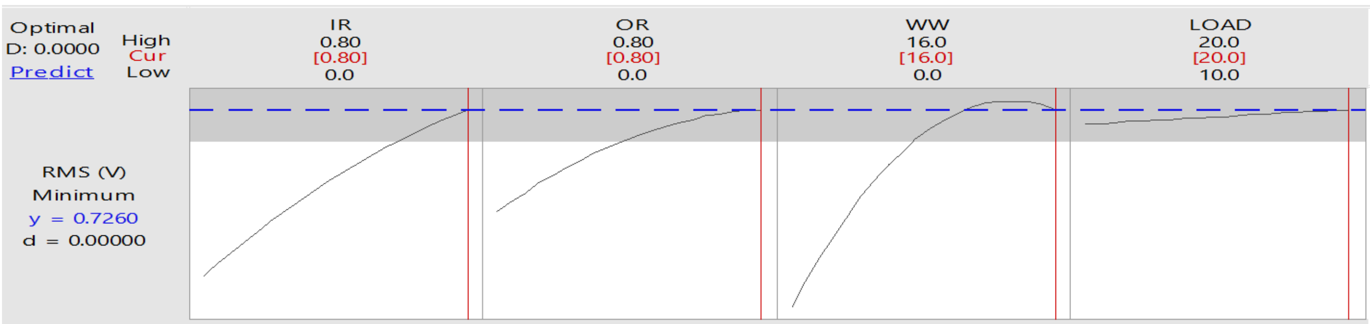
OR 0.80 [0.80] 0.0
WW 16.0 [0.0] 0.0
LOAD 20.0 [20.0] 10.0
RMS (V)
Minimum
y = 0.5648
d = 0.61507

(j)



(k)



(l)

Figure 5: A main effect plot for validation

Table 6: Validation of RMS values

Expt. no	Fault condition	IR	OR	WW	Load	Actual RMS	Predicted RMS	Percentage error
1	V FT1	0	0.8	8	10	0.607258	0.5756	5.5%
2	V FT1	0	0.8	8	20	0.623209785	0.596373	4.%5
3	V FT2	0.8	0	8	10	0.63786405	0.61186	4.25%
4	V FT2	0.8	0	8	20	0.6516432	0.62658	4%
5	V FT3	0	0.8	16	10	0.60879735	0.58821	3.5%
6	V FT3	0	0.8	16	20	0.613843278	0.590802	3.9%
7	V FT4	0.8	0	16	10	0.682192958	0.646935	5.45%
8	V FT4	0.8	0	16	20	0.665686267	0.643486	3.45%
9	V FT5	0.8	0.8	0	10	0.532961011	0.51626	3.235%
10	V FT5	0.8	0.8	0	20	0.588298687	0.56483	4.145%
11	V FT6	0.8	0.8	16	10	0.7402106	0.7138	3.7 %
12	V FT6	0.8	0.8	16	20	0.7623	0.726	5%

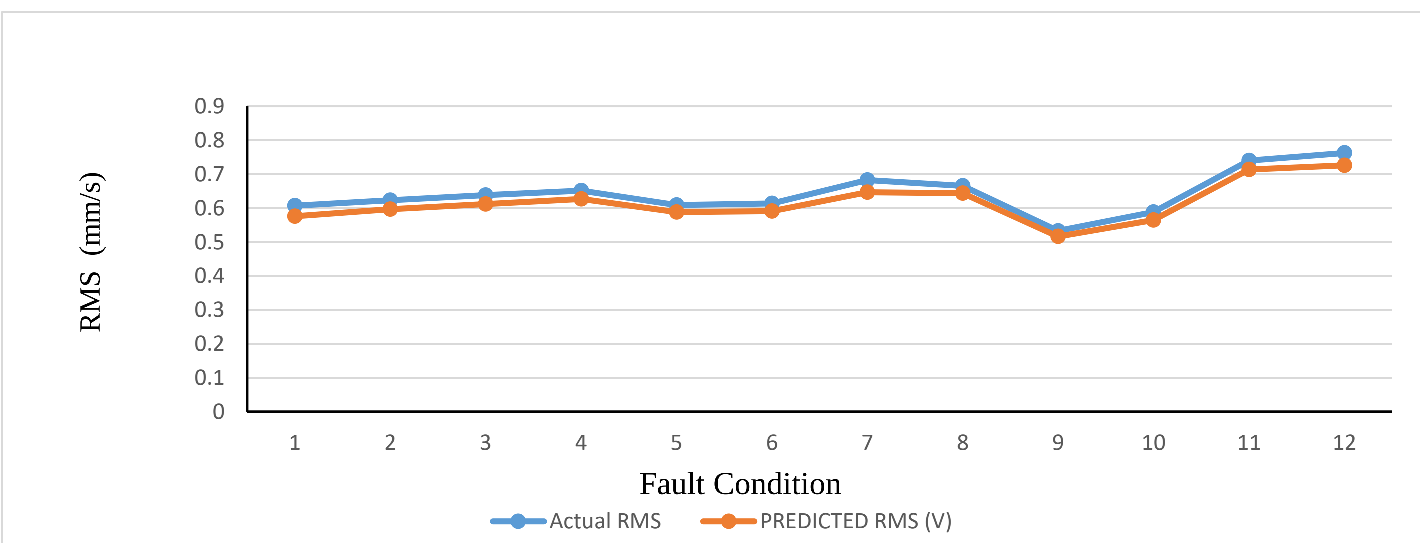


Figure 6: Actual and predicated RMS chart

VI. CONCLUSION

In the current fault analysis of the combination of worm wheel and worm wheel bearing; Box-Behnken DOE and RMS were used to study the effect of independent parameters on vibration- based RMS response. Different dimensions faults on the worm wheel bearing inner race, worm wheel outer race, the worm wheel tooth were considered. These faults and load were considered as an important independent factor to understand their effects on the RMS response of the worm gearbox. Twenty seven experimental trials were designed by applying Box-Behnken DOE. Experimental trials were performed to measure vibration-based RMS response in the vertical direction. ANOVA is used to study RMS response to determine the effectiveness of model terms. RMS response plots are plotted to analyse the influence of independent parameters with three levels.

Results proved that the response surface method using Box–Behnken design and ANOVA effective novel technique to analyse worm gearbox vibration based RMS response. The results obtained from the experiments show that RMS values extracted from the vibrations signatures captured, vary with the location of the fault. The significant change in RMS value is not recorded with increase in load from 10 kg to 20 kg. RSM analysis result shows that RMS value increases with increases in fault dimensions. Fault on the worm wheel individually or in combination with faulty bearing inner race or faulty bearing outer race influence RMS response more than faulty bearing inner race, faulty bearing outer race, or load. Regression equation in uncoded units validated as the actual RMS value and predicted RMS nearly equal with percentage error below six percent.

ACKNOWLEDGEMENTS

This work is supported by METs Institute of Engineering management Nashik and, Savitribai Phule Pune University, India.

AUTHOR CONTRIBUTIONS

R. R. Barshikar: Study conception and design, Experimentation, data collection, Manuscript Preparation. **P. R. Baviskar:** Manuscript Preparation.

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