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Condition Monitoring of Bevel Gearbox under Different Operating Conditions Using Response Surface Methodology

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Abstract

A gearbox is vital for transmitting motion and power in rotating machinery systems, and the failure in a gearbox due to faults in gears will degrade the performance, even leading to significant losses. Therefore, condition monitoring of a gearbox is vital for maintaining system performance. In the present work, condition monitoring of a bevel gearbox using response surface methodology is presented. An experimental test rig is used for experimentation with varying speed and loading conditions to obtain the vibration signals under normal and simulated defective conditions. Three input parameters, such as radial load, operating speed, and pitting defect, are considered to study the parametric effect. Time-domain Kurtosis is used as the response parameter to monitor the effects on vibrations of the gearbox due to load, operating speed, and pitting defect size. Response surface methodology (RSM), a combination of statistical and mathematical techniques, is employed to describe the relationship between the inputs and outputs of the system. The analysis of the results demonstrates the significance of the size of the pitting defect, the interaction effect of the size and load of the fault, and the interaction effect of the size and speed of the defect on system performance. It further establishes that RSM with analysis of variance (ANOVA) is a reliable method for evaluating the vital factors associated with the vibration of the gearbox.

Keywords

Condition monitoring, Vibration signal, Response surface methodology, Analysis of variance

Introduction

The gearbox is a critical constituent of rotating machinery systems. It is essential in transmitting motion and power from one rotating shaft to another and is used in various industrial applications, including automobiles, aeronautics, transportation, astronautics, and manufacturing [1-3]. However, the gears fail due to insufficient lubrication, impact load, and a harsh work environment. A sudden gearbox failure can degrade the performance and life of all rotating machinery systems, even leading to irreversible loss [4]. As a result, monitoring and controlling the gearbox's initial fault status is critical. Multiple techniques, such as vibration signal, oil debris, acoustic emission, etc., have been used to detect gearbox faults [5, 6]. Gearbox fault diagnosis using vibration signals has been the subject of extensive research for decades to identify the early deterioration of this rotating component. Vibration-based gestures convey important information about the health status of a gearbox. This information is further utilized by the application of various approaches, such as artificial neural network (ANN), random forest algorithm, fuzzy logic, Support vector machine etc., to solve industrial-based rotating system problems [7, 8]. Kankar et al. [9] used RSM to examine the impacts of several defects on the vibrations of the rotor-bearing system. The fault of rotary machinery elements was studied by Zhang et al. [10] using hybrid wavelet and integration of main component analysis and ANN to predict the situation of systems. RSM was suggested by Goyal et al. [11] for identifying the appropriate method for positioning non-contact sensors in order to successfully monitor the condition of rotating machine components. In order to examine vibration response and the impact of misalignment and unbalance on the rotor system, Prabhakar et al. [12] applied the finite element approach. They created two distinct, flexible coupling models. The coupling misalignment features of a rotor system's time domain signals are extracted using the continuous wavelet transform approach. Medina et al. [13] applied the method of symbolic dynamics analysis to detect gearbox faults using a vibration signal. They stated that the proposed algorithms could be adapted for automated monitoring systems in industrial applications to accurately and efficiently predict faults. Patil et al. [14] applied the response surface methodology to examine the relations between the ball-bearing system's various input parameters and response parameters. They studied the impact of defect size, used load and rotational speed on the vibration response as Kurtosis and reported that the defect size, the interaction effect of the size and an applied load of the defect, and the interaction effect of the size and rotational speed of the defect are relevant. Sanchez et al. [15] described a methodology for multi-fault detection in rotary systems based on K-nearest neighbours and random forest techniques. The significant features are chosen by ranking techniques such as chi-square, relief and information gain. As the determination of characteristics is generated in the time domain, this approach is useful for interactive applications. Singh et al. [16] examined the dynamic behaviour of roller bearing due to applied load, defect size and speed under normal and simulated bearing faults. Wang et al. [17] investigated novel techniques for fault diagnosis of bearing utilizing the integration of the Mahalanobis–Taguchi approach. Khoualdia et al. [18] developed a multi-objective model to predict the integrated gear bearing faults using the grey-Taguchi approach. Time and frequency features were extracted to train and test the ANN classifier. The results revealed that the methodology is applicable and fruitful for the fault diagnosis of rotating machinery.

Based on the literature reviewed above, it can be concluded that the impact of various gearbox parameters is the primary challenge for detecting incipient faults. Furthermore, their optimization minimized the dynamic characteristics of the gearbox for increased reliability and reduced system loss. As a result, the current study examines the complex characteristics of the vibration signal under normal and simulated defective conditions. A correlation between the various input parameters and response is established using RSM and ANOVA to monitor the state of the gearbox. Figure 1 depicts the steps involved in the planned RSM approach.

Materials and Methods

Experimental setup for condition monitoring

An experimental test rig (Figure 2) was developed for fault identification of the bevel gearbox under faulty simulated conditions. The experiments are performed on a bevel gearbox consisting of a 1 HP three-phase induction motor for transmitting power. The operating range of gearbox systems is from 100 to 1440 rpm, a piezoelectric accelerometer with a sensitivity of 10.19 mV/(m/s^2) and a frequency range between 1 to 4000 Hz. The data was collected for 5 seconds in each test run with 25.6 kHz sampling frequency. The information was obtained using the four-channel data acquisition kit NI 9234 and was analyzed using the Lab-VIEW National Instruments (NI) software.

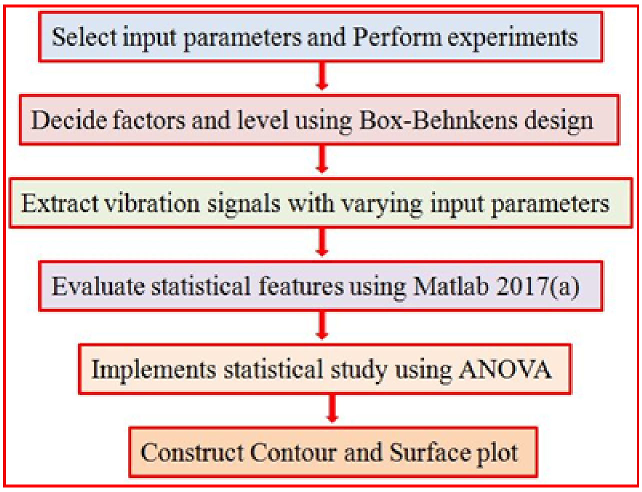


Figure 1: Flow chart of the RSM approach.

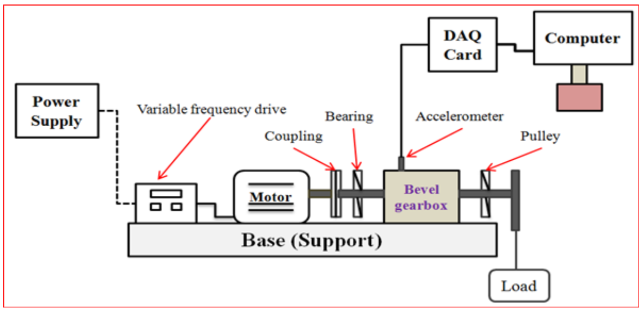


Figure 2: Schematic diagram of the experimental test rig.

The various bevel gears utilized in this experimental procedure are shown in figure 3. The simulated defects in gears were created using an Electric discharge machine on the bevel gearbox to keep the size of the defect under control.

Feature extraction

Gearbox vibrations are significantly influenced by radial load and operating speed. Studying their impact on vibrations

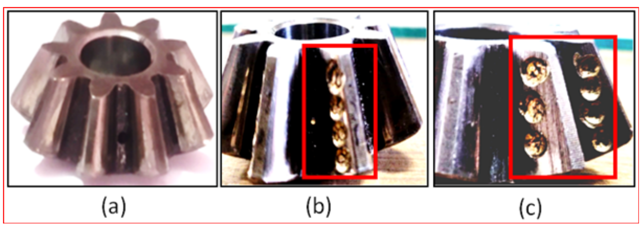


Figure 3: Bevel gear conditions: **(a)** Normal, **(b)** Slight pitting, and **(c)** Moderate pitting.

is made easier by the relationship between the load, operating speed, and pitting defect size. It has been determined from the literature that the defect size, interaction effect of impact of defect size and load, and interaction effect of load and speed are significant characteristics that have proven to be a fruitful technique to examine the important factors connected to gearbox vibrations. A critical task is to extract significant characteristics from the vibration signal to monitor the gearbox fault. Conventional statistical features are influential gear fault condition monitoring parameters that change when defects occur in the vibration signals. These statistical characteristics are easy to obtain and implement with reduced computational cost from the dynamic response. The benefit of Time domain features is that it runs more quickly and uses less memory than the frequency domain. The analysis of vibration signals in the time domain demonstrates how a signal varies over time. Under this work, the input factors are radial load, defect size, and speed. Table 1 displays the factors along with the respective levels.

Table 1: Factors and levels.

Input parameters	Levels		
	I	II	III
Pitting defect size (%)	0	12	24
Load (N)	10	30	50
Speed (rpm)	750	1000	1250

Time domain features like Kurtosis, crest factor, and RMS are frequently applied for statistical study. Kurtosis of the signal is considered the response parameter for the current study as it is regarded as a useful indicator to determine the severity of gearbox defect. It has also been reported that kurtosis features offer more accurate fault information than other response metrics [20].

Kurtosis for the vibration signal is given by (1).

$$Kurtosis = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x(i)-\mu}{\sigma}\right)^4 \tag{1}$$

Where, n is the number of vibration signal samples, $x(i)$ is the vibration amplitude of i^{th} sample, μ is the mean of vibration signal and σ is the standard deviation of vibration signal.

Response surface approach

The response surface approach is a set of mathematical and statistical algorithms for modelling and analyzing problems where multiple variables influence the response of interest. The inputs that affect the system's behaviour are denoted to as factors or variables in this context, and the outputs represent the system response generated due to the factors' contributing action. If all the input components are quantitative variables, the responses can be expressed as a function of levels and variables. This approach is commonly used for optimizing processes based on factorial designs. It refers to a process in which the response variable is determined for all probable combinations of the selected factor levels. When all other variables are held constant, the key effect of a factor is represented by the change in the response triggered by a change in the level of the factor being measured. If the result of one factor is dependent on the behaviour of other variable, it establishes an interaction (dependence) among the variables [21, 22].

In RSM, the response variable of interest (K) and the factors (y_1, y_2, ... y_n) can be specified as the function of input variables and is given by:

$$k = f(y_1, y_2, y_3........y_n) + \in \tag{2}$$

Where, $\in$ is the error in the response K. The relationship between outputs and the input components for the higher-order interaction effect and curvature in the system is generated using a second-order regression equation model for the approximation of the response surface:

$$k = \beta_o + \sum_{i=1}^{n}\beta_i y_i + \sum_{i=1}^{n}\beta_{ii} y_i^2 + \sum_{i=1,j>1}^{n}\beta_{ij} y_i y_j + \in \tag{3}$$

Where, β is the polynomial coefficient and n is the number of factors. After obtaining a response surface model, ANOVA is used to assess the model's appropriateness.

Box-Behnken designs are effective designs for fitting second-order response-surface models. Compared to central-composite designs, they only need three levels of each element; sometimes, fewer runs are required. Two-level factorial designs combined with incomplete block designs are used to create the designs. A balanced preliminary block design with three treatments and three blocks is mixed with 2^2 designs to make the final design. These designs have the advantages of being wholly spherical and requiring only three levels of factor operation [14]. There are no runs in which every factor is either at the +1 (greatest value) or -1 (lowest value) levels, which is another benefit of these designs. The design matrix and response (Kurtosis) for the bevel gearbox defect are presented in table 2.

Analysis of variance (ANOVA)

Table 2: Design matrix (Un-coded Inputs).

S. No.	Pitting condition (%)	Speed (rpm)	Load (N)	Kurtosis
1	0	750	30	3.382
2	24	750	30	4.254
3	0	1250	30	3.625
4	24	1250	30	4.640
5	0	1000	10	3.344
6	24	1000	10	4.037
7	0	1000	50	3.832
8	24	1000	50	5.202
9	12	750	10	3.292
10	12	1250	10	3.404
11	12	750	50	4.021
12	12	1250	50	4.214
13	12	1000	30	3.712
14	12	1000	30	3.694
15	12	1000	30	3.702

ANOVA is used to summaries the important effects and interactions, regression coefficients and p-value. In ANOVA analysis, the p-value determines which effects (factors and interactions) are statistically noteworthy. P-values are frequently applied in hypothesis tests to accept or reject a null hypothesis. The p-value indicates the likelihood of committing or leaving a type-I error when the null hypothesis is true. The lower the p-value, the less likely the null hypothesis will be incorrectly rejected. The cutoff value is frequently 0.05, meaning the null hypothesis is rejected when the p-value is smaller than 0.05. Further, the result is vital if the p-value is lower than 0.05 [21].

Results and Discussion

Initially, the vibration signals for different operating conditions are obtained, and from these vibration signals, Kurtosis is determined for the condition monitoring of the bevel gearbox. The statistical tool is used to examine the experimental result and their output response. ANOVA at a 95% confidence level is applied to determine the different significant terms in the model. The regression coefficient value for each response is evaluated in the coding unit in table 3. Under each response condition, interactions among different parameters are plotted as a surface response contour plot.

Incipient pitting fault using Kurtosis

The regression coefficient value in the case of incipient pitting fault (Table 3) signifies that the distinct influence of the pitting condition is statistically significant. Table 3 also shows that the corresponding p-value of pitting condition,

Table 3: Regression coefficient and P-value.

Term	Kurtosis	
	Coefficient	P-value
Constant	3.7025	0.000*
P	0.4938	0.000*
S	0.1168	0.003*
L	0.3991	0.000*
P*P	0.3219	0.000*
S*S	-0.0492	0.183
L*L	0.1586	0.055
P*S	0.0358	0.295
P*L	0.1692	0.003*
S*L	0.0202	0.539

speed and interaction effect between the pitting, load and pitting have a substantial contribution since its value <0.05.

The consequence of the ANOVA for Kurtosis for pitting conditions is presented in table 4. For Kurtosis, the R^2 and R^2-adj are 0.9952 and 0.9865, respectively, which show that the predictors of the variables superbly justify the quantity of variance in the Kurtosis value observed. In the ANOVA analysis, the linear and square terms corresponding p-values are nearer to zero, indicating that the impact of the linear and the square effects relative to the pitting condition is critical.

The interaction plots for the kurtosis value are shown in figure 4. It can be observed that the increase in the pitting condition for all loading situations leads to an increase in the kurtosis value. It is also found that the value of Kurtosis is high at higher pitting conditions and higher load values. Further, there is a significant variation in the kurtosis value at low speed under all loading conditions, but the kurtosis value becomes almost constant at high speeds. The polynomial equation of second order for Kurtosis in the form of a coded factor is given by:

Table 4: Analysis of Variance for Kurtosis.

	DF	Adj SS	Adj MS	F-value	P-value
Regression	9	3.8709	0.43011	114.82	0.000
Linear	3	3.3338	1.111	296.62	0.000
Square	3	0.4162	0.1387	37.04	0.001
Interaction	3	0.1213	0.04044	10.80	0.013
Error	5	0.0187	0.0037	-	-
Lack of fit	3	0.0185	0.00619	79.73	0.012
Pure error	2	0.0001	0.00008	-	-
Total	14	3.8897	-	-	-
R^2 - 99.52, R^2(adj) - 98.65					

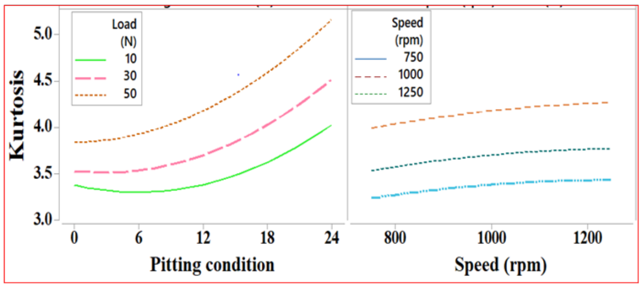
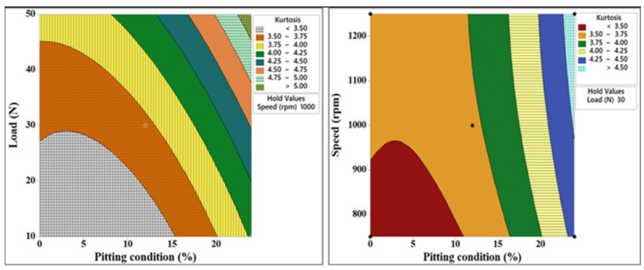


Figure 4: Kurtosis variation for Interaction plot.

Kurtosis = 2.374 - 0.0456 P + 0.00178 S - 0.00444 L + 0.002235 P*P - 0.000001 S*S + 0.000198 L*L + 0.000012 P*S + 0.000705 P*L + 0.000004 S*L.

Where, P, S and L are pitting condition, speed, and radial load, respectively.

The coded equation is necessary to identify the effect of variables by comparing the factor coefficient. The consequence of the relationship between the conditions of pitting vs load and the conditions of pitting vs speed is analyzed based on the contour plot (Figure 5) and the surface diagram (Figure 6). The results show that the rise in the pitting condition increases Kurtosis and hence, it indicates the surge in gear vibrations for a gearbox with pitting fault. The curved contour lines and the



(a) (b)

Figure 5: (a) Contour plot of Kurtosis, load vs. pitting conditions and **(b)** Contour plot of Kurtosis speed vs. pitting conditions.

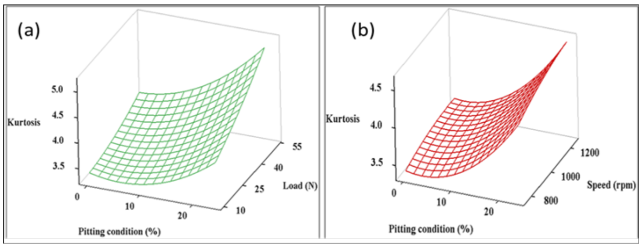


Figure 6: (a) Surface plot of Kurtosis vs. load and pitting conditions and **(b)** Surface plot of Kurtosis vs. speed and pitting conditions.

twist on the response surface suggest a substantial relationship between the pitting severity and the load that affects the response.

Conclusions

The present study examines the input parameters that affect the vibration signal of the bevel gearbox under incipient pitting conditions. RSM techniques using the Box-Behnken design and ANOVA are employed to perform the experiments. Parameters such as load, speed, and pitting defect size are chosen as input parameters for the combined parametric effect and the dynamic performance of the gearbox. Three different gear conditions with three-speed and load levels are added. Kurtosis is measured from the vibration signal under normal and faulty conditions. Response surfaces and contour plots are used to understand the dynamic actions. The following conclusions are drawn:

- The Box-Behnken architecture of the response surface technique and ANOVA has successfully evaluated the related vibration-gearbox factors.
- For a particular pitting condition, results show that the Kurtosis value increases with increase in load.
- It is also observed that the value of Kurtosis is higher at higher pitting conditions. Further, there is a significant variation in the kurtosis value at low speed under all loading conditions, but the Kurtosis value becomes almost constant at high speeds.
- These Kurtosis values can be used to assess the gearbox condition as the increase in Kurtosis indicates the surge in gear vibrations for a gearbox with pitting fault.

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None.

Conflict of Interest

The authors declare that they have no conflict of interest.

Credit Author Statement

Sheo Kumar: Conceptualization, Methodology, Resources, Investigation, Analysis, Writing - original draft preparation, Writing - review and editing; Praveen Kumar Agarwal: Conceptualization, Methodology, Writing - review and editing, Supervision. All the authors read and approved the manuscript.

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