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Optimization of sound sensor placement for condition monitoring of fixed-axis gearbox

Vanraj1*, S.S. Dhami1 and B.S. Pabla1

Abstract: Condition monitoring is expected to assist in the prevention of machine failures and enhance the reliability with lower maintenance cost. With advancement in sensor and computer technologies, it is now possible to acquire and process a large amount of machine response data in order to extract the characteristic features which provide the indication about health condition of the system. In real applications, the machine has infinite node positions but sensors can be only placed at a finite number of locations. Hence selection of optimal node positions is a challenging task and needs to be addressed. The objective of sound sensor placement optimization is to obtain a sensor layout that gives as much information of the dynamic system as possible for condition monitoring. This paper proposes a methodology for placing sound sensor on a fixed-axis gearbox to obtain high-quality information regarding the dynamic characteristics of machine. The gearbox is operated under no load and load with varying levels of gear faults and sound sensor placement positions. Loudness, loudness level, and sharpness of sound has been considered as response parameters. Mathematical relations and models between input variables and response parameters are developed. Sound sensor placement is optimized for maximum Loudness, loudness level, and sharpness values. The models are experimentally validated and tested. Results indicate that an overall accuracy of 92.2% is achieved and the approach has significant utility in industrial environment where system complexity makes the choice of sensor placement vital for condition monitoring.

ABOUT THE AUTHORS

Vanraj has multidisciplinary experimental and computational experience in a broad area of vibration and acoustics. His research team has conducted a variety of experimentation in fault diagnosis of gearbox for a variety of industrial applications. The team research projects are covering: gearbox fault diagnosis, bearing health condition monitoring, non-contact vibration analysis of rotating machines, low-cost vibration analyzer, and advanced signal processing techniques for incipient fault detection. The present paper proposes a methodology for placing sound sensor on a fixed-axis gearbox to obtain high-quality information regarding the dynamic characteristics of machine.

PUBLIC INTEREST STATEMENT

Condition monitoring is expected to assist in the prevention of machine failures and enhance the reliability with lower maintenance cost. In real applications, the machine has infinite node positions but sensors can be placed at a finite number of locations. Hence selection of optimal node positions is a challenging task and needs to be addressed. The objective of the current study is to obtain a sensor layout that gives as much information of the dynamic system as possible for condition monitoring. This paper proposes a methodology for placing sound sensor on a fixed-axis gearbox to obtain high-quality information regarding the dynamic characteristics of machine. Mathematical relations and models between input variables and response parameters are developed. Results indicate that an overall accuracy of 92.2% is achieved and the approach has significant utility in industrial environment where system complexity makes the choice of sensor placement vital for condition monitoring.
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Subjects: Optimization; Mechanical Engineering; Vibration

Keywords: optimal sensor placement; response surface methodology (RSM); fault diagnosis; sound analysis; fixed-axis gearbox

1. Introduction

Intelligent fault diagnosis system is aimed to predict the current status of the machines, which facilitate timely preventive steps to increase the reliability with lower maintenance cost. With advancement in technology, an increase in system complexity leads to increase in probability of system failure. Over more than three decades, many condition monitoring techniques have been developed which are based on measurement of dynamic responses like acoustics, vibration, eddy current, thermal fields, and radiography, acquired using various sensors which are mounted near the vicinity of the machines. Stability and accuracy of the fault diagnosis system are entirely dependent on the quality of information captured by sensors.

Gearbox plays most essential roles in the modern machinery. Most machine breakdowns, related to gearbox, are as a result of improper operating conditions and loading, hence leads to failure of the whole mechanism (Li, Yan, Yuan, Peng, & Li, 2011). For gearbox fault diagnosis, vibration is considered as a key component, thus attracting researchers toward acquiring, analyzing, and quantifying this parameter. A lot of work on condition monitoring and fault diagnosis of fixed-axis gearbox has been reported in the literature, however only a few have found their way to industrial applications. Many researches were presented the utility of vibration signatures in the anticipation of defects, but only a few emphasized on application of sound emission for the detection of faults.

Significant research has recently been conducted in speech recognition, biomedical, and ocean study applications considering sound as a parameter (Bourlard & Morgan, 2012; Hopp, Owren, & Evans, 2012; Uğuz, 2012; Xie, Jin, Krishnan, & Sattar, 2012). However, there is a huge potential to monitor the status of the machines based on sound signals. Sound-based condition monitoring provides some technical advantages over vibration-based methods. Firstly, sound sensor can be placed at a distance in either direction or periphery of the monitored system whereas vibration monitoring technique requires surface contact placement in specified direction to get accurate and meaningful information. Secondly, sound monitoring is more sensitive to certain physical processes than surface vibration, hence provides an opportunity to identify faults in early stage.

In a typical industrial environment, sound signals undergo many reflections before being absorbed, hence considering the presence of nearby reflecting surfaces is mandatory for sound-based condition monitoring of a machine. The sound conditions around machines varies with direction and locations, thus sound-based condition monitoring is generally influenced by noise generated from the surrounding environment which further lead to unreliable data. Sound attenuation could lead to inaccurate readings in lower frequency range of signals.

In order to improve the quality of sensor data, high signal-to-noise ratio needs to be maintained, which can be achieved by either appropriate selection of sensor sensitivity or by optimizing the placement of sensors. Generally, more the sensors are placed on the machine, more the information could be obtained. However, the number of sensors is strictly constrained by the high installation and maintenance cost. This issue is related to optimal sensor placement on a machine under investigation and needs to be addressed. Various efforts for optimizing the sensor placement have been reported in the literature such as effective independence based on fishers information matrix (Stephan, 2012), entropy based model parameters (Papadimitriou, Beck, & Au, 2000) in which uncertainty is computed by a Bayesian statistical methodology. A total of night sensors were studied for
nine node positions. Optimal number of sensors and node positions based on the proposed methodology were obtained. In another study, principal components analysis was implemented to find the best position of sensor (Tongpadungrod, Rhys, & Brett, 2003). Based on percentage error in position of sensor, minimum error of 3.28% was achieved. The proposed method could be used for both one- and two-dimensional surfaces. Gearbox finite-element model was investigated for sensor layout using particle swarm optimization algorithm (Hongxia, Xiuye, & Xin, 2010). The feasibility of the optimization results was verified through mode test of the finite-element modeling and characteristic analysis on the frequency response. Ten measurement positions were investigated and it was found that only four sensor positions were sufficient to provide the internal condition of the gearbox.

However, sound sensors optimal placement study for fixed axis gearbox is still relatively new. The use of Response Surface Methodology (RSM), a statistical tool, for optimizing machining parameters had showed significant results for better surface finish and tool life (Bhogal, Sindhu, Dhami, & Pabla, 2015; Saini, Chauhan, Pabla, & Dhami, 2016). There is a significant literature available which provides a strong opinion to implement the RSM technique for optimal sensor placement strategy (Liyana-Pathirana & Shahidi, 2005; Vitanov, Javaid, & Stephenson, 2010; Xiao, Wang, Zhou, Ma, & Yang, 2016).

This paper addressed RSM-based sound sensor placement optimization methodology. The main objective under the problem posed is to identify the maximum possible sound sensor node position away from the gearbox without losing characteristic information. This paper is organized as follows. Section 2 describes sensor placement as an optimization problem, in which experimental setup and data acquisition, experimental design using RSM, model generation, and analysis of the generated mathematical model are represented. Section presents influence of input variables on response parameters, generation of optimal solution, and model validation. Finally, concluding remarks are stated in section followed by research trends.

2. Sensor placement as an optimization problem
The basic idea of sensor placement optimization is to identify the optimal region in the vicinity of a machine that gives as much information of the dynamic system as possible. To realize this objective, the problem can be formulated as an optimization problem with optimizing multiple response parameters related to the system. The response parameters are expressed by a generalized equation, as a function of different input variables, and its mathematical representation is given in Equation (1) as

\[ Z = \psi(F, L, X) + \alpha \]  

subject to constraints

\[ F^b \leq F \leq F^u \]  
\[ L^b \leq L \leq L^u \]  
\[ X^b \leq X \leq X^u \]  

where \( Z \) = response parameters; \( F, L, X \) = input variables, namely fault, load, and location of sensor, respectively, ‘\( \alpha \)’ = error of the response measured, \( lb \) and \( ub \) = lower and upper bounds of respective response parameters, and \( \mathbb{R} \) = sets of real numbers.

2.1. Experimental setup and data acquisition
Figure 1(a) shows the experimental setup for condition monitoring of two stage gearbox. The setup has been designed to simulate real working conditions of a gearbox. The gearbox was driven by a 3 HP, 3-phase induction motor. The rotational speed of the setup could be varied from 100 to 3,600 rpm using variable speed drive. For external loading, magnetic particle braking system was provided with loading capacity from 0.126 to 24.85 N-m. The gearbox consists of single stage fixed axis shafts mounted with spur gears with speed reduction of 3.44:1. Table 1 summarizes the specifications of the gearbox.
For acoustic signal acquisition, three microphones with frequency range from 5 Hz to 20 kHz were used. The faults were induced on the pinion mounted on the input shaft. In this paper, depth wise damage has been simulated on the spur gear tooth by grinding the tooth in steps based on percent removal of teeth depth. A total of three conditions of the gear have been investigated: healthy gear and gear with two stages of depth wise tooth removal i.e. 30 and 50% across the tooth width as shown in Figure 1(b). For all simulated gear conditions, sound signals were acquired. The sampling frequency of the data acquisition system was 12.8 kHz and 30,000 data points were collected for each case at 2,100 rpm and each experiment is repeated five times in order to obtain the average value.

2.2. Experimental design

Gear fault (F), load (L), and location of sound sensor (x) was considered as input variables for the experimental setup to investigate the effect on response parameters viz. sound loudness \( R_1 \), loudness level \( R_2 \), and sharpness \( R_3 \) and obtain the optimized sensor location. The positions of sound sensors were varied vertically and horizontally at different sensor node positions as shown in Figure 1(c) and (d), respectively. The notations of all running condition is listed in Table 2. Three levels of gear faults were considered i.e. H, CTL30, and CTL50. Experiments were designed for two levels of load i.e. no load and 10.5 N-m load. RSM was utilized to design the experiments for different sensors.
considering three input variables with different levels as shown in Table 3. The experimental design matrix for the experimentation is shown in Table 4. The results were further analyzed using analysis of variance (ANOVA) and optimized for maximum $R_1$, $R_2$, and $R_3$ simultaneously. The Design Expert® 8.0 software package was utilized for analysis and optimization of input variables for response parameters.

3. Results and discussion
This section discusses the results obtained from the experiments conducted for the optimization of sensor location using RSM-based methodology.

3.1. Empirical model generation
RSM-based full factorial 18 experiments for each sensors were conducted. Table 5 shows the regression analysis of the responses of each sensors with standard deviation, adjusted $R^2$, and predicted $R^2$ values. The adeq precision (press) measures the signal-to-noise ratio. A ratio greater than four is desirable. Obtained press values are greater than required values hence confirms an adequate signal. These results indicate that the model is significant and provides good predictions of the outcomes. Further analysis using ANOVA for 2F1 (two-factor interaction) multi response model was performed to investigate the significance of $F$-probability value for each sensor model as shown in Table 6.

The model shows an acceptable value of $F$-probability i.e. less than 0.5 for all the sensor models, thus suggesting all the three models for different sensors to be significant. Consequently, the response equations for all the three responses for each sensor were developed as represented in Equations (2)–(10).

Sensor 1:

\[
\frac{1}{\sqrt{R_1}} = 0.11260 + 0.018842x - 3.8 \times 10^{-3}F \\
- 7.899 \times 10^{-3}L - 1.7028 \times 10^{-3}Fx \\
- 1.135 \times 10^{-3}Lx - 2.6512 \times 10^{-3}FL
\]  

Table 3. Levels of input variables selected for experimental design

| Sensor | Level          | Lowest | Center | Highest |
|--------|----------------|--------|--------|---------|
|        | Coding         |        |        |         |
| Sensor 1 | Fault          | H      | CTL30  | CTL50   |
|         | Location (position) | \(15\ \text{cm} (S_{11})\) | \(30\ \text{cm} (S_{12})\) | \(45\ \text{cm} (S_{13})\) |
|         | Load (N-m)     | 0      |        | 10.5    |
| Sensor 2 | Fault          | H      | CTL30  | CTL50   |
|         | Location (position) | \(50\ \text{cm} (S_{21})\) | \(100\ \text{cm} (S_{22})\) | \(150\ \text{cm} (S_{23})\) |
|         | Load (N-m)     | 0      |        | 10.5    |
| Sensor 3 | Fault          | H      | CTL30  | CTL50   |
|         | Location (position) | \(50\ \text{cm} (S_{31})\) | \(100\ \text{cm} (S_{32})\) | \(150\ \text{cm} (S_{33})\) |
|         | Load (N-m)     | 0      |        | 10.5    |
\[ \frac{1}{R_2} = 9.692 \times 10^{-3} + 4.5608 \times 10^{-4}x \]
\[ - 9.313 \times 10^{-5}F - 1.9169 \times 10^{-4}L \]
\[ - 3.198 \times 10^{-3}Fx - 1.3855 \times 10^{-5}Lx \]
\[ - 6.7969 \times 10^{-5}FL \]

\[ \frac{1}{R_3} = 0.22649 + 0.038410x - 7.38163 \times 10^{-3}F \]
\[ - 0.030308L \]
| Sensor no. | Source | SS | df | MS | F-value | Prob > F |
|-----------|--------|----|----|----|---------|----------|
| Sensor 1  |Model | 0.00568 | 6 6 | 0.000947 | 2.30 | 0.035 |
| Sensor 2  |Model | 0.00568 | 6 6 | 0.000947 | 2.30 | 0.035 |
| Sensor 3  |Model | 0.00568 | 6 6 | 0.000947 | 2.30 | 0.035 |

Table 6. ANOVA of 2FI model of multi response parameters
3.2. Analysis of mathematical model

The multi-response parameters were analyzed for simultaneous maximization to obtain relevant data with no loss of characteristic information, utilizing the error values obtained in actual value and the predicted value from the empirical model. Table 7 shows a maximum prediction error of 9.14% in case of $R_1$, 2.53% for $R_2$, and 8.57% being the maximum in case of predicting $R_3$ value. Thus, it has been found that the model is efficient in prediction of $R_2$, followed by $R_3$ and least for $R_1$, with overall confidence level above 95%. Moreover, the confirmation of data generated from residual curves for sensor 1 is shown in Figure 2, which represents the interaction between actual and predicted data. The proximity of all the data points to the inclined line indicates the validity of model and proves its adequacy. Predicted versus actual curve of responses for sensor 2 and sensor 3 shows the similar results (see Appendix 1).

Sensor 2:

\[
\frac{1}{R_1} = 0.026402 + 4.93 \times 10^{-3}x - 9.262 \times 10^{-4}F - 3.522 \times 10^{-3}L - 3.446 \times 10^{-4}Fx - 1.009 \times 10^{-3}Lx - 2.6788 \times 10^{-3}FL \\
(5)
\]

\[
\frac{1}{R_2} = 0.01078 + 3.196 \times 10^{-4}x - 7.8509 \times 10^{-5}F - 2.273 \times 10^{-4}L - 1.751 \times 10^{-5}Fx - 3.879 \times 10^{-5}Lx - 1.819 \times 10^{-4}FL \\
(6)
\]

\[
\frac{1}{R_3} = 0.3258 + 0.02063x - 9.267 \times 10^{-3}F - 0.0371L - 4.032 \times 10^{-4}Fx - 3.132 \times 10^{-3}Lx - 0.01723FL \\
(7)
\]

Sensor 3:

\[
\frac{1}{R_1} = 0.0254 + 5.033 \times 10^{-3}x - 5.799 \times 10^{-4}F - 3.681 \times 10^{-3}L - 5.412 \times 10^{-4}Fx - 1.066 \times 10^{-3}Lx - 2.519 \times 10^{-3}FL \\
(8)
\]

\[
\frac{1}{R_2} = 0.01072 + 3.399 \times 10^{-4}x - 5.477 \times 10^{-5}F - 2.419 \times 10^{-4}L - 3.454 \times 10^{-5}Fx - 4.003 \times 10^{-5}Lx - 1.708 \times 10^{-4}FL \\
(9)
\]

\[
\frac{1}{R_3} = 0.3228 + 0.0201x - 3.591 \times 10^{-3}F - 0.0380L - 4.758 \times 10^{-3}Fx - 3.1707 \times 10^{-3}Lx - 0.01544FL \\
(10)
\]
Table 7. Experimental design matrix for individual sensor with actual, predicted and percent error for all responses

| Sensor no. | Runs | Coded parameters | Loudness, \( R_1 \) (sone) | Loudness level, \( R_1 \) (phone) | Sharpness, \( R_1 \) (acum) |
|------------|------|------------------|----------------------------|-------------------------------|-----------------------------|
|            |      | A    | B    | C    | Actual | Predicted | % Error | Actual | Predicted | % Error | Actual | Predicted | % Error |
| Sensor 1   | 1    | -1   | -1   | -1   | 96.64  | 97.73     | -1.13   | 105.95 | 106.30    | -0.34  | 4.42   | 4.43      | -0.23   |
|            | 2    | 0    | -1   | -1   | 66.81  | 67.82     | -1.52   | 100.62 | 100.92    | -0.30  | 3.92   | 3.79      | 3.56     |
|            | 3    | 1    | -1   | -1   | 47.99  | 45.72     | 4.72    | 95.85  | 96.05     | -0.22  | 3.22   | 3.30      | 2.55     |
|            | 4    | -1   | 0    | -1   | 105.75 | 103.62    | 2.01    | 107.25 | 106.23    | 0.95   | 5.01   | 4.58      | 8.57     |
|            | 5    | 0    | 0    | -1   | 71.86  | 70.55     | 1.32    | 101.67 | 101.18    | 0.49   | 4.11   | 3.89      | 5.19     |
|            | 6    | 1    | 0    | -1   | 51.48  | 50.92     | 1.09    | 96.86  | 96.58     | 0.29   | 3.33   | 3.39      | 1.61     |
|            | 7    | -1   | 1    | -1   | 94.27  | 95.19     | -0.92   | 105.59 | 106.15    | -0.53  | 4.20   | 4.34      | 3.40     |
|            | 8    | 0    | 1    | -1   | 68.98  | 67.42     | 2.27    | 101.08 | 101.43    | -0.35  | 3.95   | 4.01      | 1.61     |
|            | 9    | 1    | 1    | -1   | 52.44  | 50.14     | 4.39    | 97.13  | 97.12     | 0.01   | 3.51   | 3.47      | 0.98     |
|            | 10   | -1   | -1   | 1    | 114.86 | 109.98    | 4.25    | 108.44 | 108.85    | -0.38  | 5.80   | 6.05      | 4.43     |
|            | 11   | 0    | -1   | 1    | 89.45  | 84.32     | 5.73    | 104.83 | 103.50    | 1.26   | 5.08   | 4.91      | 3.30     |
|            | 12   | 1    | -1   | 1    | 56.69  | 55.92     | 1.35    | 98.25  | 98.66     | -0.42  | 3.95   | 4.13      | 4.51     |
|            | 13   | -1   | 0    | 1    | 123.90 | 113.54    | 8.36    | 109.53 | 110.40    | -0.79  | 6.20   | 6.34      | 2.22     |
|            | 14   | 0    | 0    | 1    | 91.83  | 92.64     | -0.8%   | 105.21 | 105.26    | -0.05  | 5.34   | 5.10      | 4.55     |
|            | 15   | 1    | 0    | 1    | 65.93  | 64.02     | 2.90    | 100.43 | 100.58    | -0.15  | 4.05   | 4.26      | 5.13     |
|            | 16   | -1   | 1    | 1    | 158.03 | 162.33    | -2.72   | 113.04 | 111.99    | 0.93   | 6.91   | 6.65      | 3.82     |
|            | 17   | 0    | 1    | 1    | 98.83  | 99.51     | -0.68   | 106.27 | 107.07    | -0.76  | 5.13   | 5.30      | 3.21     |
|            | 18   | 1    | 1    | 1    | 78.36  | 79.10     | -0.94   | 102.92 | 102.57    | 0.34   | 4.79   | 4.40      | 8.11     |
| Sensor 2   | 1    | -1   | -1   | -1   | 44.54  | 45.69     | -2.58   | 94.77  | 94.92     | -0.16  | 2.99   | 3.02      | 1.13     |
|            | 2    | 0    | -1   | -1   | 32.53  | 35.50     | -9.14   | 90.24  | 91.65     | -1.57  | 2.73   | 2.82      | 3.26     |
|            | 3    | 1    | -1   | -1   | 29.18  | 29.02     | 0.54    | 88.67  | 88.60     | 0.08   | 2.66   | 2.64      | 0.69     |
|            | 4    | -1   | 0    | -1   | 47.13  | 43.69     | 7.28    | 95.58  | 93.85     | 1.82   | 3.15   | 2.95      | 6.31     |
|            | 5    | 0    | 0    | -1   | 34.77  | 33.42     | 3.89    | 91.20  | 90.79     | 0.45   | 2.78   | 2.76      | 0.97     |
|            | 6    | 1    | 0    | -1   | 29.51  | 27.88     | 5.52    | 88.83  | 87.93     | 1.02   | 2.59   | 2.59      | 0.13     |
|            | 7    | -1   | 1    | -1   | 37.82  | 38.34     | -1.35   | 92.41  | 92.79     | -0.41  | 2.79   | 2.88      | 3.05     |
|            | 8    | 0    | 1    | -1   | 29.46  | 31.57     | -7.14   | 88.81  | 89.95     | -1.28  | 2.65   | 2.70      | 1.63     |
|            | 9    | 1    | 1    | -1   | 26.59  | 26.83     | -0.88   | 87.33  | 87.27     | 0.07   | 2.56   | 2.54      | 1.00     |
|            | 10   | -1   | -1   | 1    | 46.15  | 45.01     | 2.47    | 95.28  | 95.04     | 0.25   | 3.36   | 3.36      | 0.05     |
|            | 11   | 0    | -1   | 1    | 37.51  | 37.76     | -0.66   | 92.29  | 92.42     | -0.14  | 3.23   | 3.17      | 1.65     |
|            | 12   | 1    | -1   | 1    | 34.06  | 32.52     | 4.54    | 90.90  | 89.94     | 1.06   | 3.07   | 3.00      | 2.29     |
|            | 13   | -1   | 0    | 1    | 54.35  | 52.75     | 2.94    | 97.64  | 97.29     | 0.36   | 3.65   | 3.69      | 0.90     |
|            | 14   | 0    | 0    | 1    | 39.81  | 42.71     | -7.28   | 93.15  | 94.70     | -1.67  | 3.30   | 3.46      | 4.97     |

(Continued)
| Sensor no. | Runs | Coded parameters | Loudness, $R_1$ (sone) | Loudness level, $R_2$ (phone) | Sharpness, $R_3$ (acum) |
|-----------|------|-----------------|------------------------|-------------------------------|--------------------------|
|           |      | A   | B   | C   | Actual | Predicted | % Error | Actual | Predicted | % Error | Actual | Predicted | % Error |
| 15        | 1    | 0   | 1   | 1   | 34.90  | 37.31     | −6.92   | 91.25  | 92.25     | −1.09   | 3.17   | 3.27      | −0.87   |
| 16        | −1   | 1   | 1   | 1   | 64.16  | 63.71     | 0.70    | 100.04 | 99.64     | 0.39    | 4.17   | 4.08      | 0.20    |
| 17        | 0    | 1   | 1   | 1   | 51.84  | 51.88     | −0.08   | 96.96  | 97.10     | −0.14   | 3.85   | 3.81      | 0.04    |
| 18        | 1    | 1   | 1   | 1   | 47.22  | 43.76     | 7.33    | 95.61  | 94.68     | 0.98    | 3.64   | 3.58      | 0.74    |
| Sensor 3  |      |     |     |     |        |           |         |        |           |         |        |           |         |
| 1         | −1   | −1  | −1  | −1  | 47.16  | 48.69     | −3.52   | 95.59  | 95.87     | −0.28   | 3.14   | 3.12      | 0.02    |
| 2         | 0    | −1  | −1  | −1  | 33.09  | 34.79     | −5.16   | 90.48  | 92.20     | −1.90   | 2.76   | 2.87      | −0.91   |
| 3         | 1    | −1  | −1  | −1  | 29.49  | 29.57     | −0.08   | 88.82  | 88.81     | 0.01    | 2.65   | 2.65      | 0.00    |
| 4         | −1   | 0   | −1  | −1  | 51.82  | 47.44     | 4.44    | 96.95  | 94.50     | 2.53    | 3.13   | 2.96      | 0.97    |
| 5         | 0    | 0   | −1  | −1  | 34.52  | 34.34     | 0.51    | 91.09  | 91.23     | −0.15   | 2.74   | 2.77      | −0.17   |
| 6         | 1    | 0   | −1  | −1  | 31.76  | 29.39     | 1.67    | 89.89  | 88.17     | 1.72    | 2.66   | 2.60      | 0.60    |
| 7         | −1   | 1   | −1  | −1  | 39.38  | 39.22     | 0.16    | 92.99  | 93.18     | −0.20   | 2.79   | 2.82      | −0.13   |
| 8         | 0    | 1   | −1  | −1  | 29.00  | 31.20     | −7.20   | 88.58  | 90.27     | −1.70   | 2.58   | 2.68      | −1.10   |
| 9         | 1    | 1   | −1  | −1  | 26.95  | 27.31     | −0.36   | 87.52  | 87.54     | −0.02   | 2.61   | 2.56      | 0.05    |
| 10        | −1   | −1  | 1   | 1   | 52.67  | 49.15     | 6.68    | 97.19  | 94.44     | 0.75    | 3.56   | 3.55      | 0.04    |
| 11        | 0    | −1  | 1   | 1   | 37.04  | 40.23     | −8.39   | 92.11  | 93.43     | −1.32   | 3.23   | 3.29      | −0.73   |
| 12        | 1    | −1  | 1   | 1   | 35.69  | 34.06     | 2.46    | 91.57  | 90.60     | 0.97    | 3.19   | 3.07      | 0.72    |
| 13        | −1   | 0   | 1   | 1   | 61.09  | 56.21     | 7.78    | 99.33  | 98.25     | 1.08    | 3.78   | 3.73      | 0.55    |
| 14        | 0    | 0   | 1   | 1   | 40.68  | 42.96     | −5.28   | 93.46  | 94.44     | −0.98   | 3.34   | 3.31      | 0.03    |
| 15        | 1    | 0   | 1   | 1   | 39.31  | 38.88     | 0.53    | 92.97  | 92.78     | 0.20    | 3.28   | 3.21      | −0.77   |
| 16        | −1   | 1   | 1   | 1   | 66.33  | 65.66     | 0.67    | 100.52 | 100.13    | 0.38    | 4.07   | 3.94      | 0.13    |
| 17        | 0    | 1   | 1   | 1   | 51.13  | 53.60     | −4.47   | 96.76  | 97.54     | −0.80   | 3.70   | 3.76      | −0.60   |
| 18        | 1    | 1   | 1   | 1   | 48.13  | 45.29     | 5.91    | 95.89  | 95.08     | 0.81    | 3.66   | 3.60      | 0.66    |

Table 7. (Continued)
The mathematical models developed for each sensor using RSM were analyzed and were found significant for all response parameters. The effects of various input parameters on individual response parameters were studied to analyze the level of influence and are listed in Table 8. The results have been represented graphically and comparison charts were generated accordingly. Finally, the desired conditions for optimization were simultaneously evaluated for predicting the optimal results.

3.3. Influence of input variables on response parameters

The input variables, that is, location, fault, and load, were analyzed to study their individual effect on \( R_1 \), \( R_2 \), and \( R_3 \). The results were represented in the form of multidimensional curves representing varied slopes, thus indicating variation in level of influence on individual response variables.

The loudness of sound signal is a perceptual measure of the effect of the energy content of sound, which is directly connected to the change in physical system (Arnold, 1980, Harris, 1991). Figure 3(a) and (b) shows the effect of location and fault at minimum and maximum load on \( R_1 \) for sensor 1.

Figure 3(c) indicates that the sensor location is the most influential factor for \( R_1 \), as the slope is found to be maximum for this case. The increase in load is the next most influential parameter in increasing \( R_1 \) value followed by fault. \( R_1 \) shows a decreasing trend with an increase in location. Table 8 lists the values of \( R_1 \) at different points shown in Figure 3(a) and (b). An increase of 20.5 and 51.03% in value of \( R_1 \) for point A and B, respectively, was observed which demonstrate the effectiveness of load for fault identification. For sensor 2 and sensor 3, similar trending behavior of \( R_1 \) was observed (see Appendices 2 and 3). However, the maximum amplitude of \( R_1 \) for sensor 2 and sensor 3 decreased as compared to sensor 1. The reason behind this is the near field position of sensor 1 as compared to far-field position of sensor 2 and sensor 3.

Loudness level of sound signals was measured to depict the sound amplitude in a particular frequency band of interest, which shows change in gear-mesh frequency amplitude. Hence any change
in gear-mesh frequency and its harmonics directly influence the loudness level. Figure 4(a) and (b) shows the effect of location and fault for maximum and minimum load on $R_2$ for sensor 1. Figure 4(c) shows that sensor location exhibits maximum influence on $R_2$ followed by load and fault. Table 8 lists the values of $R_2$ at different points shown in Figure 4(a)–(b). An increase of 2.71 and 5.50% in value of $R_2$ for point C and D, respectively, was observed which indicate enhancement of fault frequency identification under load using loudness level. However, a linear increasing trend of $R_2$ value with increasing fault was observed for both minimum and maximum loads. Similar trend of $R_2$ was observed for sensor 2 and sensor 3 (see Appendices 2 and 3).

![Figure 3. Effect of input parameters on $R_1$ for sensor 1.](image)

![Table 8. Effect of input parameters on response variables for sensor 1](table)

| Response parameter | Point | Status                  | Value  |
|--------------------|-------|-------------------------|--------|
| $R_1$ (sone)       | A     | minimum L and F, maximum x | 48.67  |
|                    | B     | minimum L, maximum F and x | 97.89  |
|                    | A’    | minimum F, maximum L and x | 58.65  |
|                    | B’    | maximum F, L and x       | 147.85 |
| $R_1$ (phone)      | C     | minimum L and F, maximum x | 96.05  |
|                    | D     | minimum L, maximum F and x | 106.15 |
|                    | C’    | minimum F, maximum L and x | 98.66  |
|                    | D’    | maximum F, L and x       | 111.99 |
| $R_1$ (acum)       | E     | minimum L and F, maximum x | 3.30   |
|                    | F     | minimum L, maximum F and x | 4.73   |
|                    | E’    | minimum F, maximum L and x | 4.132  |
|                    | F’    | maximum F, L and x       | 6.64   |
Figure 4. Effect of input parameters on $R^2$ for sensor 1.

(a) 3D graph showing effect of $x$ and $F$ at minimum $L$

(b) 3D graph showing effect of $x$ and $F$ at maximum $L$

(c) Perturbation curve

Figure 5. Effect of input parameters on $R^3$ for sensor 1.

(a) 3D graph showing effect of $x$ and $F$ at minimum $L$

(b) 3D graph showing effect of $x$ and $F$ at maximum $L$

(c) Perturbation curve
The sharpness of sound signal reflects the ratio of high frequency level to overall level. Sounds that exhibit higher energy in high frequencies tend to be sharper. It is a crucial parameter which is physically detected by human ears. In general, for any change in physical system properties, there is a noticeable change in sharpness of sound. From perturbation curve shown in Figure 5(c), the sensor location is the most influential factor with negative slope for $R_3$ as sensor location transition from near-field position to free-field position thereby dissipating higher energy component to the surroundings. However, load tends to increase $R_3$ in the presence of fault as faulty teeth mesh with healthy teeth with more impact thereby generating high-energy frequency component as shown in Figure 5(b). Table 8 list the values of $R_3$ at different points shown in Figure 5(a)–(b). An increase of 25.21 and 40.38% in value of $R_3$ for point E and F, respectively, was observed indicating load effectiveness with increasing fault. Similar trend of $R_3$ was observed for sensor 2 and sensor 3 (see Appendix 2).

### 3.4. Optimal solution generation

The effect of all the input factors on individual responses was modeled. However, to obtain the maximum information about the condition of gearbox, all these response parameters needed to be maximized based on input variables. Also, it is necessary to find the maximum possible sensor node position away from the gearbox that can be achieved without compromising the information loss. Considering that an optimal solution was developed for maximum $R_1$, maximum $R_2$, and maximum $R_3$. For this, varied conditions of input variables were modeled and tested. The models which generated an overall highest desirability for all the responses simultaneously were with maximum sensor location, in-range fault, and in-range load. The optimal values thus obtained for sensor 1 are 24-cm vertical location, CTL50 fault, and 10.5 N-m load. For sensor 2 and sensor 3, the values are 112.5-cm horizontal location, CTL50 fault, and 10.5 N-m load.
3.5. Model validation

The set of input parameters for individual sensors were computed for the optimal model generation and were experimentally validated. For the individual sensors, three repetitions of experiments were performed and the average value for each response parameters was considered. The results were compared with those predicted by the RSM model. The graphical representation of optimal solutions obtained experimentally, compared with predicted responses is shown in Figure 6. The results showed a maximum of 7.8% error in case of R1. So, an overall accuracy of 92.2% was achieved.

4. Conclusion

Sensor placement is of key importance in condition monitoring of gearbox. In the present work, RSM-based sound sensor location optimization scheme is presented. The optimization accounts for maximum sensor location, both in horizontal and vertical directions, to maximize the loudness, loudness level, and sharpness considering load on the gearbox and fault in gear as input variables. The approach is designed such that maximum dynamic information of the system can be retained for the fault diagnosis of gearbox. The use of statistical modeling technique for predicting multi-process factors to find the optimal sensor location is an effective technique. All response parameters viz. loudness, loudness level, and sharpness are influenced mostly by sensor location, which indicates critical information loss as distance increases. Load on the system enhances the fault information as there is an increase in response parameters at maximum load conditions for all considered ranges of faults. The optimal model for maximum loudness, maximum loudness level, and maximum sharpness was envisaged, and out of various possible models, the one with maximum sensor location with in-range load and in-range fault was selected. The responses proposed by the optimal model were at 24-cm vertical sensor location and 112.5-cm horizontal location with maximum fault and maximum load. Finally, the authenticity of model was confirmed experimentally and a maximum error of 7.8% was obtained, which suggested an acceptable liaison with the predicted model. Thus, the utilization of RSM for finding optimal sensor location is recommended.

5. Research trends

Future research may focus on testing of proposed methodology for various types of faults (e.g. root crack) to demonstrate the generalization of the sensor placement optimization using RSM in the reliable classification of various faults. Authors also suggest to evaluate the robustness of the methodology using field data collected in real-world applications where other rotating machines are working near the vicinity of the testing machine. The proposed method can be employed in non stationary operation like robot condition monitoring.

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**Appendix 1. Predicted vs. actual curve of responses for sensor 2 and sensor 3**

![Figure A1. Sensor 2 predicted versus actual curve for all three responses.](image-url)
Figure A2. Sensor 3 predicted versus actual curve for all three responses.

Appendix 2. Graphical representation of effects of input parameters for sensor 2 and sensor 3

Figure B1. Effect of input parameters on $R_1$ for sensor 2.

(a) 3D graph showing effect of $x$ and $F$ at minimum $L$
(b) 3D graph showing effect of $x$ and $F$ at maximum $L$
(c) perturbation curve
Figure B2. Effect of input parameters on $R^2$ for sensor 2.

(a) 3D graph showing effect of $x$ and $F$ at minimum $L$

(b) 3D graph showing effect of $x$ and $F$ at maximum $L$

(c) perturbation curve
Figure B3. Effect of input parameters on $R_3$ for sensor 2.

(a) 3D graph showing effect of $x$ and $F$ at minimum $L$

(b) 3D graph showing effect of $x$ and $F$ at maximum $L$

(c) perturbation curve
Figure B4. Effect of input parameters on $R_1$ for sensor 3.

(a) 3D graph showing effect of x and F at minimum L

(b) 3D graph showing effect of x and F at maximum L

(c) perturbation curve
Figure B5. Effect of input parameters on $R^2$ for sensor 3.

(a) 3D graph showing effect of x and F at minimum L

(b) 3D graph showing effect of x and F at maximum L

(c) perturbation curve
Figure B6. Effect of input parameters on $R_3$ for sensor 3.

(a) 3D graph showing effect of x and F at minimum L

(b) 3D graph showing effect of x and F at maximum L

(c) perturbation curve

Appendix 3. Tabular representation of effects of input parameters for sensor 2 and sensor 3

| Response parameter | Point | Status | Value |
|--------------------|-------|--------|-------|
| $R_1$ (sone)       | G     | minimum L and F, maximum x | 29.02 |
|                    | H     | minimum L, maximum F and x | 38.34 |
|                    | G'    | minimum F, maximum L and x | 32.51 |
|                    | H'    | maximum F, L and x | 63.71 |
| $R_2$ (phone)      | I     | minimum L and F, maximum x | 88.59 |
|                    | J     | minimum L, maximum F and x | 92.79 |
|                    | J'    | minimum F, maximum L and x | 89.94 |
|                    | J''   | maximum F, L and x | 99.64 |
| $R_3$ (acum)       | K     | minimum L and F, maximum x | 2.63 |
|                    | L     | minimum L, maximum F and x | 2.87 |
|                    | K'    | minimum F, maximum L and x | 3.00 |
|                    | L'    | maximum F, L and x | 4.07 |
### Table C2. Effect of input parameters on response variables for sensor 3

| Response parameter | Point | Status | Value |
|--------------------|-------|--------|-------|
| $R_i$ (sone)       | M     | minimum L and F, maximum x | 29.56 |
|                    | N     | minimum L, maximum F and x | 39.21 |
|                    | $M'$  | minimum F, maximum L and x | 34.05 |
|                    | $N'$  | maximum F, L and x         | 65.65 |
| $R_i$ (phone)      | O     | minimum L and F, maximum x | 88.82 |
|                    | P     | minimum L, maximum F and x | 93.17 |
|                    | $O'$  | minimum F, maximum L and x | 90.59 |
|                    | $P'$  | maximum F, L and x         | 100.13|
| $R_i$ (acum)       | Q     | minimum L and F, maximum x | 2.65  |
|                    | R     | minimum L, maximum F and x | 2.82  |
|                    | $Q'$  | minimum F, maximum L and x | 3.07  |
|                    | $R'$  | maximum F, L and x         | 3.94  |