



VIBRATIONAL ANALYSIS OF GEAR DRIVE USING MACHINE LEARNING

¹ AKASH BHADANE, ² SAHIL KANWALU, ³ VEDANT BIDGAR, ⁴ ADITYA RAHINJ
⁵ Mrs. Ami R. Barot ⁶ Dr.P.G.Kulkarni

Abstract

This thesis presents a comprehensive examination of the vibration analysis of spur gear drives. Spur gears are widely utilized in various mechanical systems due to their simplicity, efficiency, and cost-effectiveness. However, the dynamic behaviour of gears under different loads and operating conditions can result in vibration and noise problems, which may lead to premature failure of the gears and othersystem components. Therefore, it is crucial to analyse the vibration characteristics of spur gear drivesto ensure reliable and efficient operation. In this study, we investigate the vibration behaviour of spurgear drives using experimental techniques. By analysing the vibration signals with various signal processing methods, we extract frequency and amplitude information. Additionally, we examine the influence of different parameters such as mean, median, mode, kurtosis, skewness, entropy, and RMS value on the vibration behaviour of spur gears. Our findings reveal that these parameters significantlyimpact the vibration behaviour of spur gears. Furthermore, we analyse the dynamic behaviour of the entire mechanical system using LABVIEW software. Through simulation results, we gain a better understanding of the dynamic behaviour of gears, aiding in the optimization of design parameters to minimize vibration. By studying the vibration characteristics and employing advanced analysis techniques, we aim to ensure the reliable and efficient operation of spur gear drives, reducing the likelihood of premature failure and improving overall system performance.

Keywords: mean, median, mode, kurtosis, skewness, entropy, RMS value, Experimental Setup, Fault Diagnosis, Vibration Analysis, Lab View Software, Decision Tree, Random Forest, KNN algorithm.

I. Introduction

Gears play a vital role in various industrial applications, such as gearboxes and machine tools. The failure of gears can lead to significant financial losses. Therefore, ensuring their proper functioning has become increasingly crucial in recent years. One of the commonly used methods for detecting andpreventing gear faults is vibration analysis. Vibration analysis has gained popularity due to its effectiveness in early fault detection and prevention. It involves examining the vibrations produced by rotating machinery and structures to assess their operational conditions and status. These vibrations can originate from various sources, including rotating shafts, gear teeth meshing, rolling bearing elements, rotating electric fields, fluid flows, combustion events, structural resonance, and angular rotations.

Several vibration analysis techniques are widely employed for gearbox diagnosis. These techniques include waveform analysis, time-frequency analysis, fast Fourier transform (FFT), spectral analysis, order analysis, time synchronous average, and probability density moments. Each technique offers unique insights into the condition of the gears and helps identify potential faults at an early stage.

By utilizing these vibration analysis techniques, engineers and maintenance professionals can effectively monitor the health of gears in gearboxes and other machinery. This proactive approach enables them to detect faults before they escalate into more severe issues, leading to costly downtimeand repairs.

1.1 Vibration Analysis

Vibration analysis is a technique used to monitor and analyze the patterns of vibrations in a signal. It involves studying both the time waveform and the frequency spectrum of the signal. In the time domain analysis, recorded vibration waveforms are examined to identify abnormal vibration



events and understand their occurrence. Various parameters such as root-mean-square (RMS), peak amplitude, standard deviation, kurtosis, crest factor, and skewness are used to assess the condition of the monitored targets. This analysis provides an overall evaluation of the targets' health status. However, in complex machines with multiple components, the vibration signals consist of a mixture of vibrations from each rotating component. This makes it challenging to analyze the condition of critical components like gears, bearings, and shafts using only time waveforms. Therefore, frequency spectrum analysis is essential in real-world applications, particularly in rotating machinery, in addition to time domain analysis. Vibration analysis can be conducted in both the time domain and the frequency domain. Time domain analysis is employed to monitor vibration levels and establish acceptable operation vibration limits. If these limits are exceeded, it may indicate a deterioration in the overall health condition of the machine and the development of defects. On the other hand, frequency domain analysis is effective in detecting abnormal vibration patterns that may be hidden or masked by other vibrations in the time waveform. For example, it can identify the periodic collisions caused by a crack on a roller bearing outer race. By analyzing the frequency spectrum, the periodicity of these collisions can be detected, leading to the identification of bearing faults.

1.2 Machine Learning Overview

Currently, vibration analysis has evolved to incorporate machine learning techniques, which offer a modern approach for automating the process of learning from input data and making decisions without heavy reliance on human intervention. In this particular study, the focus is on evaluating the effectiveness of a machine learning-based system for diagnosing gear faults, specifically misalignment and broken teeth. The study does not consider combinations of these defects. The experimental setup involves a paired spur gear shaft, driven by a variable speed motor with a belt drive, and a data acquisition system for capturing vibrational signals. Vibration signals from three classes, including signals from a healthy gear, were collected. TensorFlow, a popular machine learning framework, was employed to implement the machine learning models. The proposed method successfully detects gear defects while the machine is operating, and it offers speed and automation, thereby minimizing the need for human intervention.

II. SCOPE

- a. To identify faults in gears and replace it with healthy gear.
- b. To remove faulty gears by analyzing vibrations.
- c. To avoid the catastrophic failure in the whole system.
- d. To increase safety standards of gear drive machines.
- e. Vibration analysis is a valuable tool for ensuring the reliability of gear drives. By identifying and addressing problems early, vibration analysis can help to prevent costly downtime and equipment failures.
- f. Vibration analysis is a non-destructive method of detecting and assessing the condition of rotating machinery. It is used to identify problems with gears, bearings, shafts, and other components before they cause a failure.

III. EXPERIMENTAL SETUP (DESIGN OF GEARDRIVE)

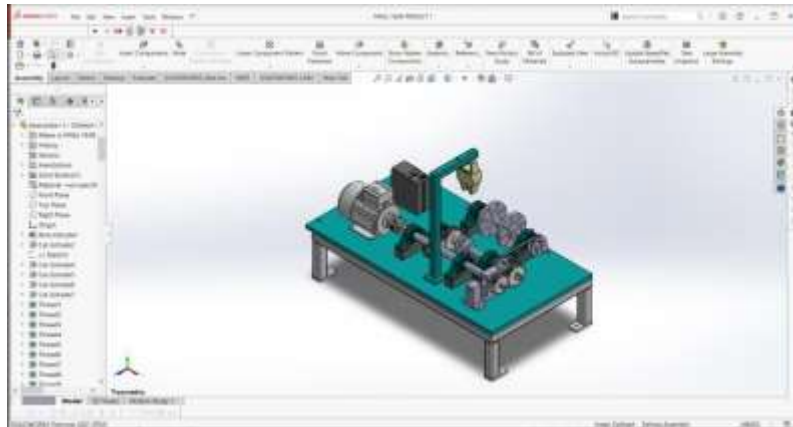


Fig.1: Experimental Setup in Solid works

In the above setup the motor is connected to the shaft. Shaft is rotated at some speed. Four spur gears are mounted on the shaft & each shaft contains two gears. The spur gears are meshed. P205 (Pillow Bearing) is used to support shaft and for smooth rotation. The VFD is used to control the speed of the motor. Do vibrational analysis of healthy and faulty gear using Fast Fourier transformer (FFT). In LabVIEW first we get vibration graph with respect to time domain then we will convert it into frequency domain. Then compare the graph of both gears. We can able to analyse faulty and healthy gear.



Fig.1.1: Experimental Setup with accelerometer mounted on it



Fig.1.2: Experimental Setup



Fig.1.3: Finding speed with the help of Tachometer

IV. COMPONENT SPECIFICATIONS

4.1 GEARS



Fig.2: Gears

Gears play a crucial role in various industrial applications, such as machine tools and gearboxes. However, unexpected gear failure can result in significant economic losses. To prevent such failures, researchers have focused on fault diagnosis in gears. Vibration signal analysis is a widely used technique for detecting faults in rotating machinery, and it can also be used to detect faults in gears. By analysing the vibration signal of a gearbox, engineers can identify the signature of faults in the gears and perform early fault detection using various signal processing techniques. This paper provides a review of current vibration analysis techniques for monitoring gear condition.

4.1.1 Gear 1



Fig.3: Gear 1

Specifications:

- Number of teeth's (n): 26
- Module(m): 3.175
- Pressure angle: 20
- Quantity: 2
- Material: En24

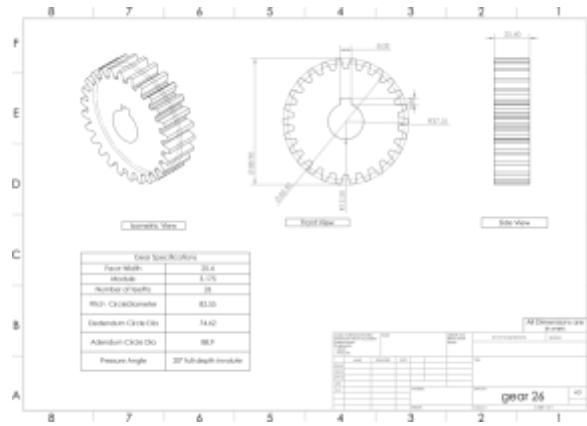


Fig.4: CAD drawing of Gear 1

4.1.2 Gear 2



Fig.5: Gear 2

Specifications:

- Number of teeth's (n): 22
- Module(m): 3.175
- Pressure angle: 20
- Quantity: 2
- Material: En24

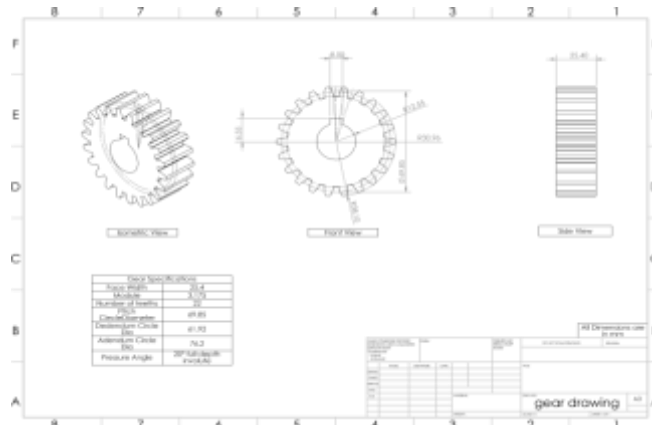


Fig.6: CAD drawing of Gear 2

4.2 Bearing

A bearing is a component used in machinery that limits any undesirable motion and minimizes



friction between the moving parts. It can enable linear or rotational movement or control the forces acting on the moving parts. The design of bearings aims to facilitate the desired motion while reducing friction. They are generally categorized based on the type of operation, allowed motions, or the directions of the applied loads.



Fig.7: Pillow Bearing(P205)

Specifications:

- Name of Bearing: P205 (pillow bearing)
- Inner Diameter: 25mm
- Width: 34mm
- Quantity: 4

4.3 Motor

An induction motor is an AC electric motor that uses electromagnetic induction to produce torque in the rotor without the need for electrical connections. The rotor can be either wound or squirrel-cage type. Three-phase squirrel-cage induction motors are commonly used in industrial drives due to their self-starting capability, reliability, and cost-effectiveness. Single-phase induction motors are suitable for smaller loads like household appliances. Induction motors were traditionally used for fixed-speed applications but are now used with variable-frequency drives for variable-speed service, providing energy savings in applications like centrifugal fans, pumps, and compressors.



Fig.9: Induction Motor

Specifications:

- 3 Phase Induction Motor
- Power: 0.5hp
- Rpm: 1410
- Efficiency: 71%

4.4 Variable Frequency Drive (VFD)

A variable-frequency drive (VFD) is an electro-mechanical device utilized to regulate the speed and torque of AC motors by adjusting the frequency of the motor input. VFDs can also vary voltage or current, depending on the specific design. They are employed in a wide range of devices, from small appliances to large compressors. With the implementation of more stringent emission standards and the growing demand for enhanced reliability and availability, electric drive systems utilizing VFDs have garnered increased interest. These systems offer superior efficiency compared to traditional methods that rely on throttling control of fluid flow, such as pumps with damper control for fans. Despite these advantages, VFDs have yet to achieve significant market penetration globally across all their applications.



Fig.10: VFD

Specifications:

- Model No.: Mitsubishi D700, AC Drive, 1KW-500KW, Three Phase
- Cost: 9500

V. Calculations

5.1 Gear parameter for 22 teeth

- Pressure Angle (ϕ) = 20°
- Module(m)= 3.175
- Teeth(z) = 22

Terms	Symbol	Formula	Value (mm)
Pitch circle diameter	d	Z*m	69.8500
Addendum	h_a	1.00*m	3.1750
Dedendum	h_f	1.25*m	3.9687
Tooth depth	H	2.25*m	7.1437

Addendum Diameter	d_a	$d + 2*m$	76.2000
Dedendum Diameter	d_f	$d - 2.5*m$	63.5000

Table No 1 : Calculation For 22 Tooth Gear

5.2 Gear parameter for 26 teeth

- Pressure Angle (ϕ) = 20°
- Module(m)= 3.175
- Teeth(z) = 26

Terms	Symbol	Formula	Value (mm)
Pitch circle diameter	d	$Z*m$	82.5500
Addendum	h_a	$1.00*m$	3.1750
Dedendum	h_f	$1.25*m$	3.9687
Tooth depth	H	$2.25*m$	7.1437
Addendum Diameter	d_a	$d + 2*m$	88.9000
Dedendum Diameter	d_f	$d - 2.5*m$	74.6125

Table No 2 : Calculation For 26 Tooth Gear

VI. Lab View Setup

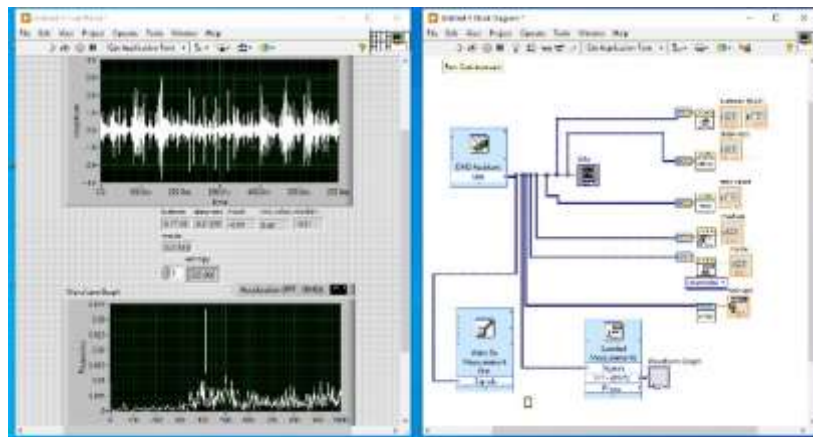


Fig.11: Lab View Setup

LabVIEW is a graphical programming environment commonly utilized by engineers to create automated systems for research, validation, and production testing. It is particularly well-suited for tasks such as data acquisition, instrument control, and industrial automation. In our specific application using LabVIEW version 2022, we employ feature extraction techniques. Feature extraction involves deriving meaningful information or characteristics from a given dataset.

6.1 Feature Extraction Using LabVIEW Software

Mean: The mean is a measure of central tendency that represents the average value of a dataset. It is computed by adding up all the values and dividing the sum by the total number of values.

Mode: The mode is a measure of central tendency that identifies the value(s) that appear most frequently in a dataset. A dataset can have multiple modes, or it may have no mode if all values occur with the same frequency.

Median: The median is a measure of central tendency that indicates the middle value of a dataset. To determine the median, the data is arranged in ascending or descending order, and the value that lies exactly in the middle is identified. In the case of an even number of values, the median is calculated as the average of the two middle values.



Skewness: Skewness quantifies the asymmetry of a probability distribution. A symmetric distribution has a skewness of zero. If a distribution exhibits a longer tail on one side, it is considered skewed in that direction. Skewness can be positive (longer right tail) or negative (longer left tail).

Kurtosis: Kurtosis measures the "peakness" of a probability distribution. A distribution with high kurtosis is characterized by a tall and narrow peak, indicating a greater concentration of data points around the mean.

Entropy: Entropy gauges the amount of uncertainty or randomness present in a probability distribution. It is computed as the sum of the probability of each possible outcome multiplied by the logarithm of that probability.

RMS value: RMS, or root mean square, represents the average value of a varying set of values over time. In the context of electrical engineering, it is used to calculate the effective voltage or current of an AC signal. The RMS value is derived by taking the square root of the mean of the squared values of the signal over a specific time period.

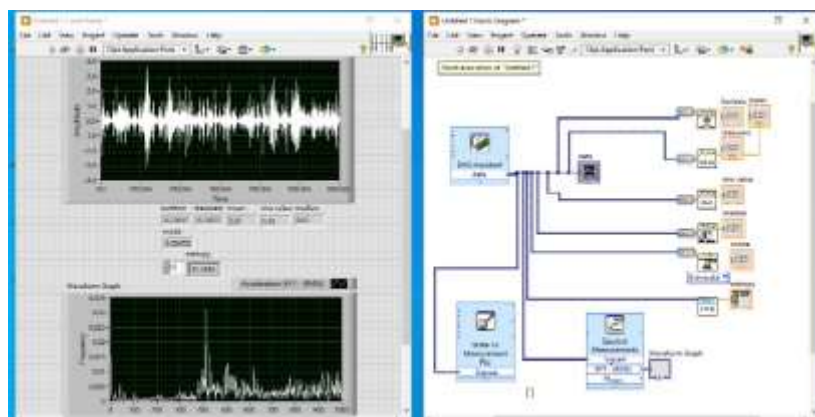
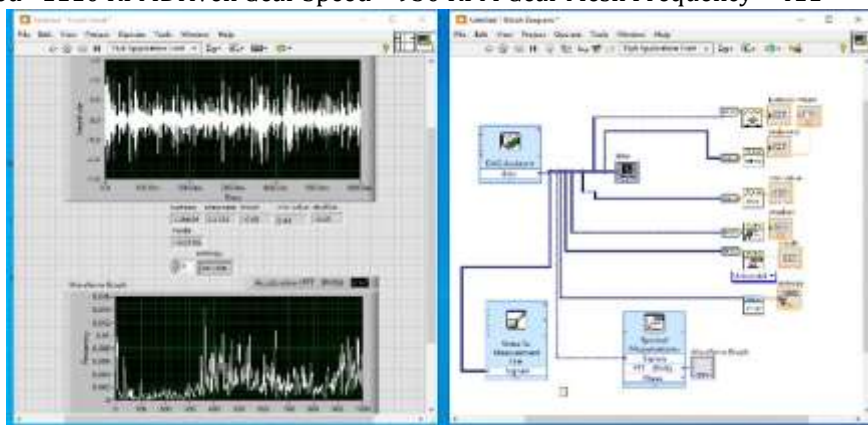
6.2.1 25% Defect Gear Analysis

1. Driving Gear speed – 1010 RPM

Driven Gear Speed – 810 RPM Gear Mesh

Frequency – 351

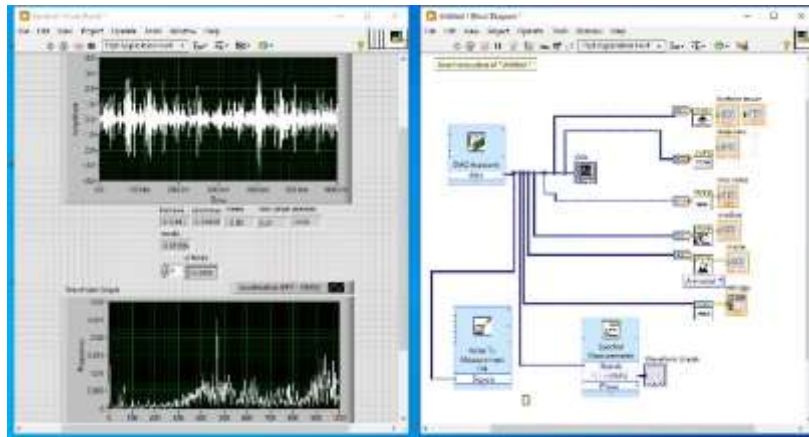
Driving Gear speed – 1110 RPM Driven Gear Speed – 950 RPM Gear Mesh Frequency – 411



2. Driving Gear speed – 1270 RPM

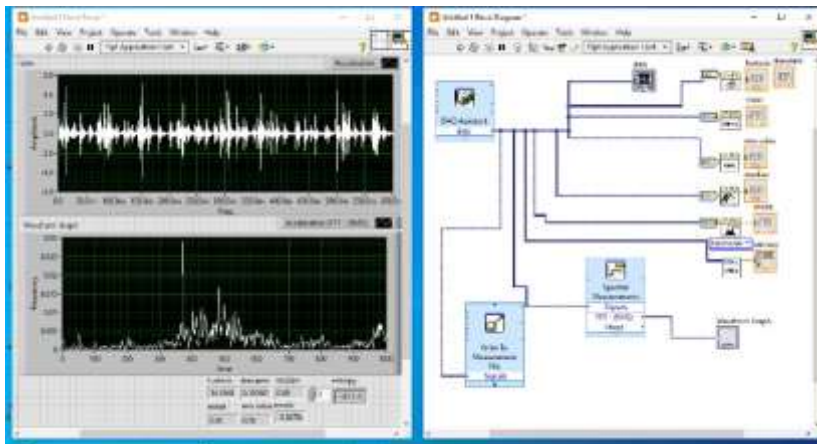
Driven Gear Speed – 1050 RPM Gear Mesh

Frequency – 455

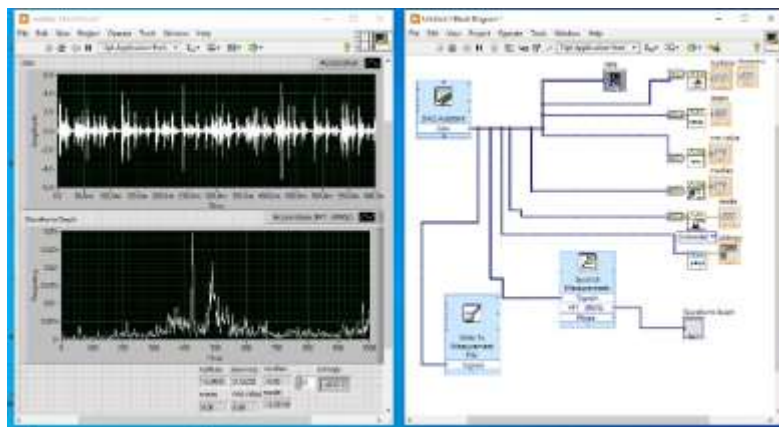


6.2.2 100% Defect Gear Analysis

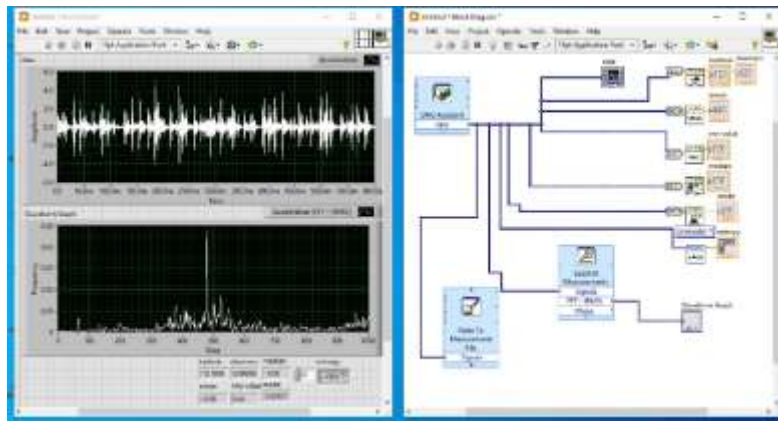
1. Driving Gear speed – 1110 RPM
Driven Gear Speed – 850 RPM
Gear Mesh Frequency – 368



2. Driving Gear speed – 1150 RPM
Driven Gear Speed – 970 RPM
Gear Mesh Frequency – 420

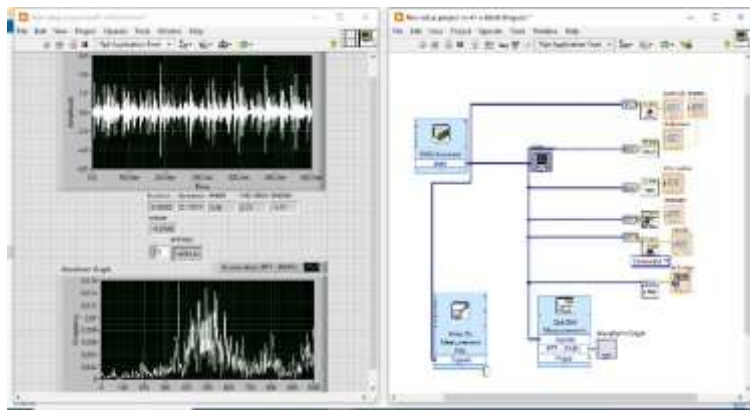


3. Driving Gear speed – 1302 RPM
Driven Gear Speed – 1102 RPM
Gear Mesh Frequency – 477

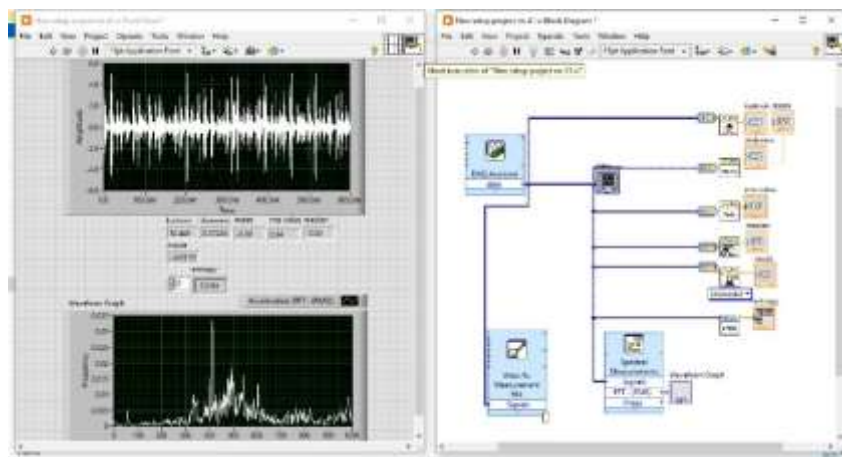


6.2.3 Healthy Gear Analysis

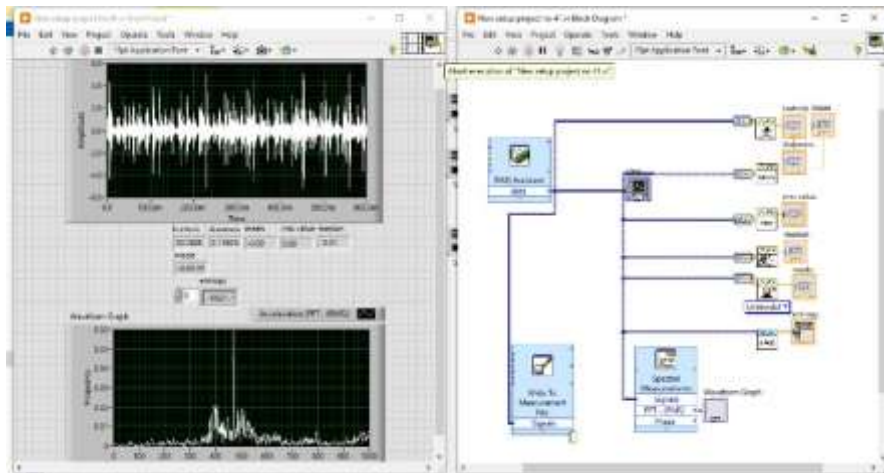
1. Driving Gear speed –980 RPM
Driven Gear Speed – 830 RPM
Gear Mesh Frequency – 360



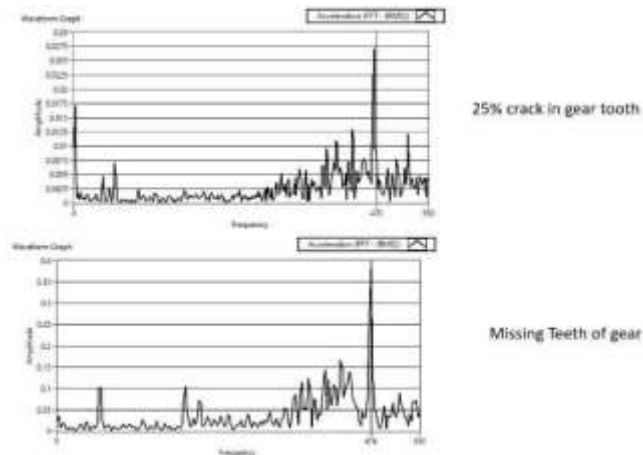
2. Driving Gear speed –1130 RPM
Driven Gear Speed – 960 RPM
Gear Mesh Frequency – 416



3. Driving Gear speed – 1280 RPM
Driven Gear Speed – 1080 RPM
Gear Mesh Frequency – 469



VII. Gear Mesh Frequency Graph



VIII. RESULT AND DISCUSSION

A. By performing the experiments the following tables are obtained

1. For 25% tooth Faulty Gear

Speed	25% Crack	
	Kurtosis	Maximum
700	6.1385	2.3485
840	7.1169	2.7211
980	7.9255	3.6255

Table No 3 : For 25% tooth Faulty Gear

2. For 100% tooth Faulty Gear

Speed	100% Crack	
	Kurtosis	Maximum
700	8.1710	3.5411
840	8.3230	4.777
980	10.0886	4.9042

3. For Healthy Gear

Table No 4 : For 100% tooth Faulty Gear

Speed	100% Crack	
	Kurtosis	Maximum
700	8.1710	3.5411
840	8.3230	4.777
980	10.0886	4.9042

700	3.3453	5.1166
840	4.1967	5.1166
980	4.6795	5.1166

Table No 5 : For Healthy Gear

B. The below graphs are obtained using these results. The plotted graph shows the comparison between the Healthy Gear, 25% Tooth faulty Gear, 100% Tooth faulty gear

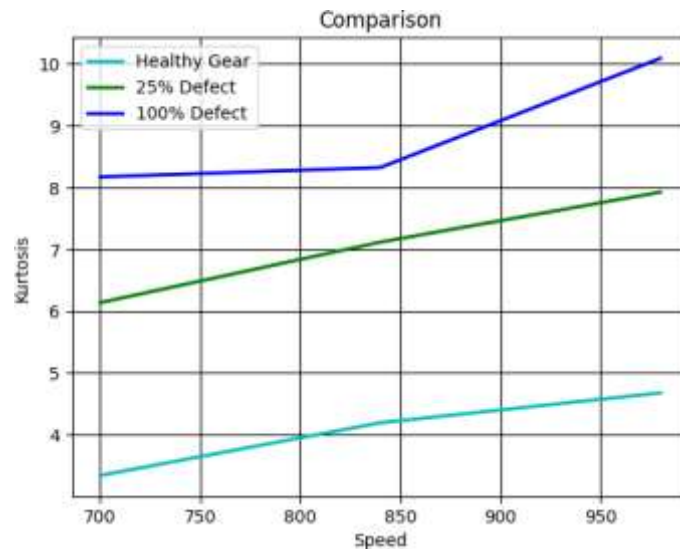


Fig No 12 : Analysis Of Gear Fault Depend on Kurtosis

From the graph plotted between kurtosis and speed, it is observed that for Healthy Gear the value of kurtosis is between 1 to 5, for 25% Defect the value of Kurtosis is between 6 to 8 and for 100% Defect the value of Kurtosis is between 8 to 11.

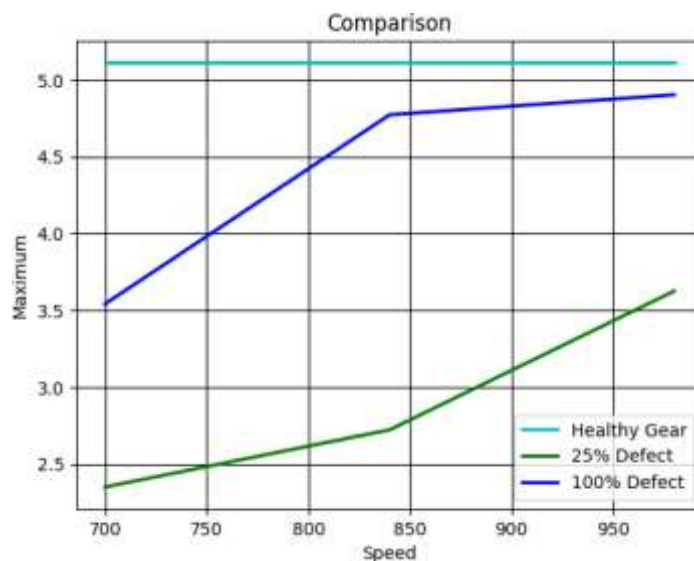


Fig No 13 : Analysis Of Gear Fault Depend on Maximum

From the graph plotted between Maximum and speed, it is observed that for Healthy Gear the value of Maximum is constant, for 25% Defect the value of Maximum is between 1 to 3.5 and for 100% Defect the value of Maximum is between 3.5 to 5



IX. MACHINE LEARNING

DETAILS Training Model :-

- MULTICLASS

```
import pickle
import pandas as pd
import numpy as np
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import f1_score
from sklearn.model_selection import KFold, StratifiedKFold, cross_val_score

from warnings import simplefilter
from sklearn.metrics import roc_auc_score
```

```
df = pd.read_csv("F:\Zr People\Sahil kanwal\Dataset.csv")
df.head()
```

Sr No	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	
0	1	0.000406	0.006016	-0.001604	5.116662	0.745537	0.555825	7.008035	0.12441
-1	2	0.000406	0.006016	-0.001604	5.116662	0.745537	0.555825	7.008035	0.12441
2	3	-0.001353	0.005534	-0.004972	5.116662	0.685849	0.470389	7.429619	0.09411
3	4	0.000094	0.005627	-0.005442	0.051157	0.697393	0.486357	6.138570	0.07041

```
print(df.columns)
```

```
Index(['Sr No', 'Mean', 'Standard Error', 'Median', 'Mode', 'Standard Deviation', 'Sample Variance', 'Kurtosis', 'Skewness', 'Range', 'Minimum', 'Maximum', 'Sum', 'Count', 'Gear', 'y_val'], dtype='object')
```

```
print(df.describe())
```

	Sr No	Mean	Standard Error	Median	Mode
count	300.000000	300.000000	300.000000	300.000000	300.000000
mean	150.500000	-0.001055	0.004817	-0.004079	1.327799
std	86.746758	0.009621	0.001248	0.009992	2.545344
min	1.000000	-0.045593	0.003085	-0.050585	-5.117423
25%	75.750000	-0.002285	0.003771	-0.006231	-0.056209
50%	150.500000	-0.000453	0.004584	-0.003250	0.052651
75%	225.250000	0.001331	0.005719	-0.000611	5.116662
max	300.000000	0.037519	0.007841	0.034806	5.116662

	Standard Deviation	Sample Variance	Kurtosis	Skewness
count	300.000000	300.000000	300.000000	300.000000
mean	0.597038	0.380294	6.690369	0.173284
std	0.154660	0.199965	2.011276	0.002239
min	0.382381	0.146215	2.563405	0.009370
25%	0.467310	0.218379	5.367296	0.113053
50%	0.568125	0.322766	6.635274	0.158203
75%	0.708809	0.502411	7.972852	0.231248
max	0.971802	0.944400	13.381982	0.382534

	Range	Minimum	Maximum	Sum	Count
count	300.000000	300.000000	300.000000	300.000000	300.000000
mean	8.189982	-3.909273	4.280709	-16.202386	15359.300000
std	1.960841	1.037887	0.947077	147.765351	0.459023
min	4.004026	-5.117423	2.112150	-700.259490	15359.000000
25%	6.290110	-4.938353	3.458999	-35.101045	15359.000000
50%	8.873835	-4.112147	4.762783	-6.953713	15359.000000
75%	10.055015	-2.885239	5.116662	20.449421	15360.000000
max	10.234084	-1.891876	5.116662	576.252127	15360.000000

	y_val
count	300.000000
mean	40.000000
std	40.688062
min	0.000000
25%	0.000000
50%	25.000000
75%	100.000000
max	100.000000

```
print(df.info())

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300 entries, 0 to 299
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ---
 0   Sr No                 300 non-null   int64
 1   Mean                  300 non-null   float64
 2   Standard Error        300 non-null   float64
 3   Median                300 non-null   float64
 4   Mode                  300 non-null   float64
 5   Standard Deviation    300 non-null   float64
 6   Sample Variance       300 non-null   float64
 7   Kurtosis              300 non-null   float64
 8   Skewness              300 non-null   float64
 9   Range                 300 non-null   float64
10   Minimum               300 non-null   float64
11   Maximum               300 non-null   float64
12   Sum                   300 non-null   float64
13   Count                 300 non-null   int64
14   Gear                  300 non-null   object
15   y_val                 300 non-null   int64
dtypes: float64(12), int64(3), object(1)
memory usage: 37.6+ KB
None

int_columns=df.select_dtypes(include='int')
float_columns=df.select_dtypes(include='float')

print(float_columns.columns)
print()
print(cat_columns.columns)

Index(['Sr No', 'Count', 'y_val'], dtype='object')

Index(['Mean', 'Standard Error', 'Median', 'Mode', 'Standard Deviation',
       'Sample Variance', 'Kurtosis', 'Skewness', 'Range', 'Minimum',
       'Maximum', 'Sum'],
      dtype='object')

Index(['Gear'], dtype='object')

from sklearn.preprocessing import LabelEncoder
lab=LabelEncoder()
df['category']=lab.fit_transform(df['y_val'])
df['Class'] = df['y_val']
df['class']=lab.fit_transform(df['Class'])
df['Gear'] = lab.fit_transform(df['Gear'])

print(df.info())

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300 entries, 0 to 299
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype
---  ---
 0   Sr No                 300 non-null   int64
 1   Mean                  300 non-null   float64
 2   Standard Error        300 non-null   float64
 3   Median                300 non-null   float64
 4   Mode                  300 non-null   float64
 5   Standard Deviation    300 non-null   float64
 6   Sample Variance       300 non-null   float64
 7   Kurtosis              300 non-null   float64
 8   Skewness              300 non-null   float64
 9   Range                 300 non-null   float64
10   Minimum               300 non-null   float64
11   Maximum               300 non-null   float64
12   Sum                   300 non-null   float64
13   Count                 300 non-null   int64
14   Gear                  300 non-null   int32
15   y_val                 300 non-null   int64
16   category              300 non-null   int64
17   Class                 300 non-null   int64
18   class                 300 non-null   int64
dtypes: float64(12), int32(1), int64(6)
memory usage: 43.5 KB
None

corr_matrix = df.corr().abs()
```




```
C:\Anaconda\lib\site-packages\sklearn\neighbors\_classification.py:211: FutureWarning: Unlike other reduction functions (e.g. 'skew
mode, _ = stats.mode(y[neigh_ind, k], axis=1)
```

```
print(metrics.classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.90	0.87	0.89	31
1	1.00	0.85	0.92	33
2	0.72	0.88	0.79	26
accuracy			0.87	90
macro avg	0.87	0.87	0.87	90
weighted avg	0.88	0.87	0.87	90

▼ Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
```

```
reg_dt = DecisionTreeClassifier()
reg_dt.fit(x_train, y_train)
y_pred = reg_dt.predict(x_test)
print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.9
```

```
print(metrics.classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.94	1.00	0.97	31
1	0.84	0.97	0.90	33
2	0.95	0.69	0.80	26
accuracy			0.90	90
macro avg	0.91	0.89	0.89	90
weighted avg	0.91	0.90	0.90	90

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print('Confusion matrix\n\n', cm)
```

```
Confusion matrix:
```

```
[[31  0  0]
 [ 0 32  1]
 [ 2  6 18]]
```

```
filename = 'dt_model.sav'
pickle.dump(reg_dt, open(filename, 'wb'))
```



Testing Model

```
import pickle

loaded_model = pickle.load(open('dt_model.sav', 'rb'))

GCB = 0 GCC = 1 GCD = 2 GCE = 3

Find = [[0.000406243,0.006015721,-0.001001698,5.116661841,0.745530089,0.555025253,7.000034916,0.124413657,10.23400437,-5.117422531,5.1104
, 0],
[-0.000494607,0.003242793,-0.004681753,-0.289369506,0.401883979,0.161510733,3.824600653,0.224291637,4.720000738,-2.34253464,2.386366097,-
],
[-0.001810506,0.004909106,-0.004573783,0.100889554,0.088412351,0.170165501,7.760445187,0.161419673,8.736228778,-4.020656529,4.715572249,-
]]

0 means 0% 1 means 25% 2 means 100%

k = loaded_model.predict(Find)
print(k)

[0 1 2]
```

CONCLUSIONS

1. Successfully Design and Arrange the setup of gear drive in Solid works 2021 Software.
2. Successfully manufactured Gear drive setup.
3. Successfully analyse Vibration Produced in Gear Drive with healthy and faulty gear.
4. Fault Detection: The vibration analysis also facilitated the detection of any potential faults or abnormalities within the gear drive system. By monitoring and analysing vibration with the help of LabVIEW software, any early signs of gear wear, misalignment, or bearing defects were identified. Timely detection of these faults allows for proactive maintenance and minimizes the risk of catastrophic failures.
5. As the Fault in the Gear increases the value of kurtosis increases.
6. As the Fault in the Gear increases the value of Maximum value increases but for Healthy Gear it is constant.
7. In Machine Learning process it is found that Random Forest algorithm gives 93% accuracy, KNN algorithm gives 87% accuracy and Decision Tree algorithm gives 90% accuracy.
8. So, Random Forest algorithm is the best algorithm to train and test the dataset of Gear Drive.

X. ACKNOWLEDGEMENT

We are acknowledging Mr. S.B. Kolpe & Mr. Deepak Patil (Applied Hydraulic & Pneumatics Pvt. Ltd) Prof. Dr. P.G. Kulkarni (Project Guide, Mechanical Department, PVG's COET, Pune), Prof. Ami Barot (Project Guide, Mechanical Department, PVG's COET, Pune), Prof. Dr. M. M. Bhoomkar (HOD Mechanical Department, PVG's COET, Pune) for kind guidance and support

XI. REFERENCES

- [1] "VIBRATION ANALYSIS TECHNIQUES FOR GEARBOX DIAGNOSTIC: A REVIEW" By Amit Aherwar, Md. Saifullah Khalid
- [2] "Detection of Fault in Gear Box System using Vibration Analysis Method" By L.S. Dhamande, A.C. Pawar and V.J. Suryawanshi
- [3] "A Review of Gearbox Condition Monitoring Based on vibration Analysis Techniques Diagnostics and Prognostics" By Abdulrahman S. Sait, Yahya I. Sharaf-Eldeen
- [4] "Vibration Analysis and Control in Mechanical Structures and Wind Energy Conversion Systems" by Paolo Gardonio and Leonardo Lanari



- [5] "Mechanical Vibrations: Theory and Application to Structural Dynamics" by Michel Geradin and Daniel J. Rixen
- [6] "Review of Gearbox Condition Monitoring Based on vibration Analysis Techniques Diagnostics and Prognostics" by Deepam Goyal, Vanraj B. S. Pabla, S. S. Dhama
- [7] "Detection of Fault in Gearbox System Using Vibration Analysis Method" by Saurabh S. Shahapurkar and Others
- [8] "Dynamic Modelling and Vibration Analysis for Gear Tooth Crack Detection" by Omar Dawood Mohammed
- [9] "Fault Detection of Gear Using Spectrum and Cepstrum Analysis" by KIRAN VERNEKAR, HEMANTHA KUMAR and K V GANGADHARAN
- [10] "Spur Gear Fault Diagnosis using a Multilayer Gated Recurrent Unit Approach with Vibration Signal" by Ying Tao and Others
- [11] "Fault Detection of Two Stage Spur Gearbox using Time Domain Technique: Effect of Tooth Breakage and Improper Chamfering" by Shrikant Shukla, Vijay Kumar Karma
- [12] "Gearbox faults feature selection and severity classification using machine learning" By Ninoslav Zuber, Rusmir Bajrić
- [13] "Vibration Analysis for Machine Monitoring and Diagnosis: A Systematic Review" by Mohamad Hazwan, Mohd Ghazali & Wan Rahiman
- [14] "Vibration Analysis and Control in Mechanical Structures and Wind Energy Conversion Systems" by Paolo Gardonio and Leonardo Lanari
- [15] "Mechanical Vibrations: Theory and Application to Structural Dynamics" by Michel Geradin and Daniel J. Rixen
- [16] [https://www.twi-global.com/technical-knowledge/faqs/vibration analysis](https://www.twi-global.com/technical-knowledge/faqs/vibration-analysis)