PREDICTIVE MAINTENANCE OF HELICAL GEAR USING IOT FOR VARING SPEED

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College *: The National Institute of Engineering, Mysuru*
Branch *: Department of Mechanical Engineering*
Guide(S) *: Mr. Ravikiran*
Student(S) *: Mr. Dore Prasad R.*
Mr. Harshit R. K.
Ms. Disha V.
Ms. Harshitha S.

Keywords

IOT – Internet of Things
FT – Fourier Transform
EMD – Empirical Mode Decomposition
IMF – Intrinsic Mode Functions
SVM – Support Vector Machine
RMS – Root Mean Square

Introduction/ Background

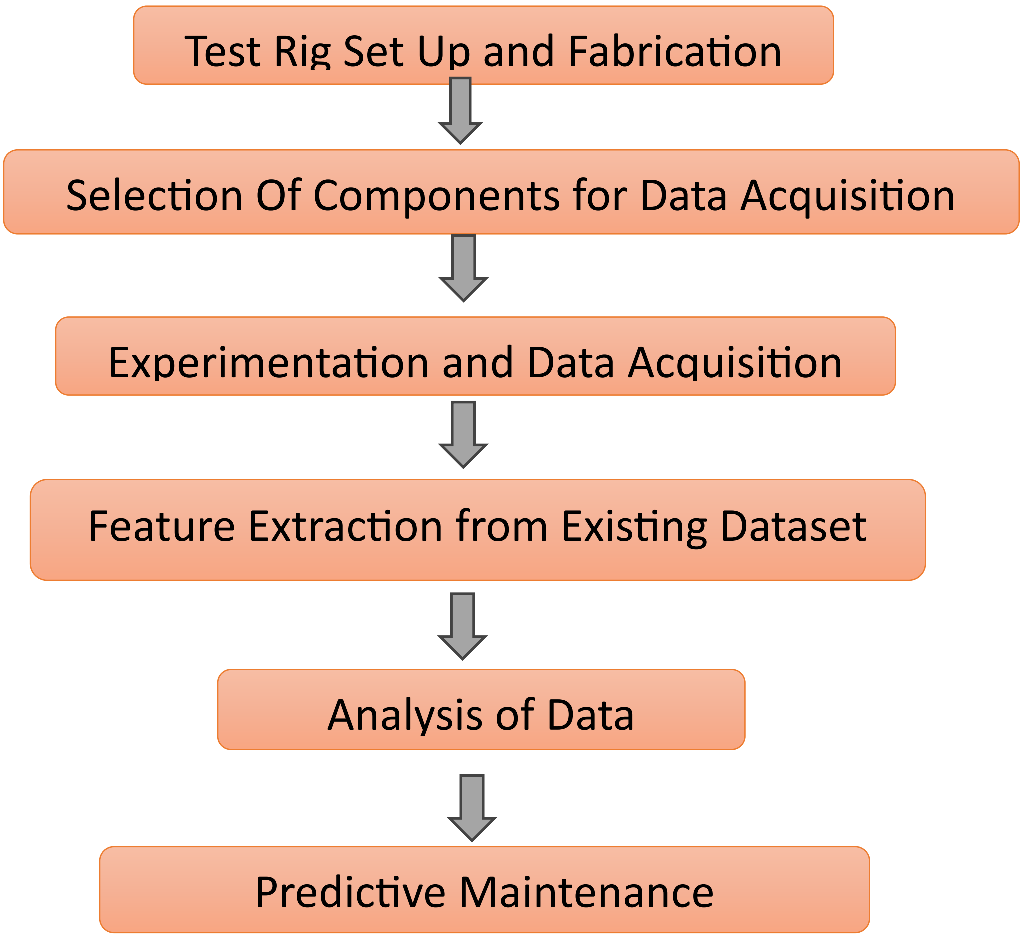
Gearboxes have many advantages such as compact structure, low friction, high transmission efficiency, and stable transmission ratio. Thanks to these unique metrics, and gearboxes are widely used as transmission systems in wind turbines, ships, vehicles, and advanced manufacturing. However, gearbox transmission systems usually operate in harsh working environments, which makes the bearing and gear subject to fatigue and failure. gearbox fatigue and failure can cause a sudden shutdown of the transmission system and bring unexpected economic loss, and even serious accidents. Therefore, it is necessary to monitor the health status of gearbox transmission systems so that proper maintenance strategies can be scheduled in advance, which can significantly benefit industry practices and safety operations.

Vibration analysis is crucial for monitoring the health of rotating machinery, like gearboxes. Using accelerometers, vibrations from both healthy and damaged components are captured, revealing valuable mechanical insights. Initially, Fourier Transform (FT) was used for analysis but lacked simultaneous time and frequency localization. To overcome this, the Empirical Mode Decomposition (EMD) method was introduced. EMD decomposes non-stationary, non-linear signals into Intrinsic Mode Functions (IMFs), which represent different oscillatory modes in the signal, enabling precise analysis of its characteristics over time. For fault detection and diagnosis, algorithms like Support Vector Machine (SVM) are widely used. SVM classifies data by creating boundaries between different classes, using feature vectors extracted from vibration signals. A recent study employed time-domain analysis on experimental data, extracting features such as Root Mean Square (RMS), Kurtosis, and Skewness using MATLAB. These features were then classified into fault categories using a machine learning classification learner. In essence, vibration analysis deciphers the condition of gearboxes by examining their vibrations. Advanced methods like EMD and SVM allow for accurate fault detection and diagnosis, ensuring machinery reliability and efficiency, and reducing downtime and maintenance costs.

a) Objectives

- The main purpose of monitoring gear is to detect a fault, or a degradation process, that has reached a certain symptomatic level and to provide an indication of the abnormality in time before the functional breakdown occurs.
- Predictive maintenance allows an asset to be consistently monitored, which helps to determine a maintenance plan tailored for each individual asset.
- It anticipates potential issues by analyzing data for varying speeds, enabling timely interventions to prevent failures, minimize downtime, extend gear lifespan, and enhance operational efficiency.
- This approach contributes to maximizing the life of an asset while simultaneously reducing maintenance costs.

b) Methodology



Materials: -

Pinion	**teeth**
Gear	**teeth**
Module	**2**
Material	**Cast iron grade 20 (pinion and gear)**
Gear ratio	**1:2**

Gear ratio chosen was 1:2. Material for both driven and driving gear was chosen. For gear and pinion selected material was Cast Iron grade 20. For all the test cases like worn teeth ,50% worn teeth all were implicated on pinion. After design of gear, based on maximum bending moment and different load acting on the shafts. Material of the solid shaft was selected as EN-24 and diameter of 20mm

Material	**EN-24**
Diameter	**20mm**

Based on the above design appropriate bearing was selected considering centre distance between shafts and diameter of shaft. Bearing selected was model no. UCPH 204 pillow block bearing

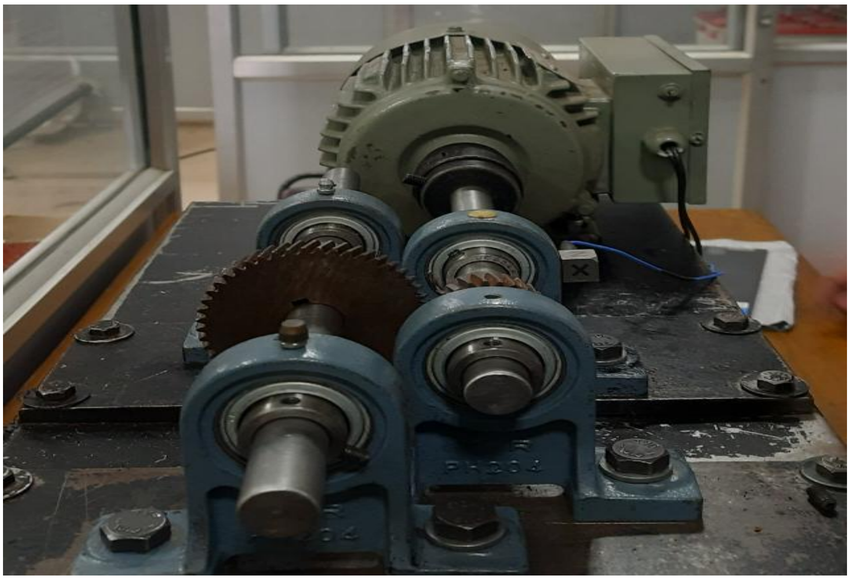
Type	**Pillow block**
Model No	**UCPH 204**
Static load rating	**6650N**
Dynamic load rating	**12750N**

Motor selection, after design of gear and shaft, based on requirement of Speed (RPM), Torque needed to be transmitted, Power rating, motor selection was done. Selected had following specification

Type	**Single phase 4 pole induction motor (1 HP)**
Frequency	**50hz**
RPM	**1425**

Voltage regulator was selected based on motor specification

Model name	**Xcluma Scr voltageregulator**
Power rating	**4000W**
Voltage rating	**~220V**
Current rating	**Up to 25A**



For Wet Condition

Properties of lubrication oil, Gear Transmission oil was used for lubrication purposes to ensure smoother performance.

Oil Name	**HYLUBE EXTRA 20W 40**
Viscosity	**110**
Operating Temperature	**-20^{o}c to 180^{o}c**

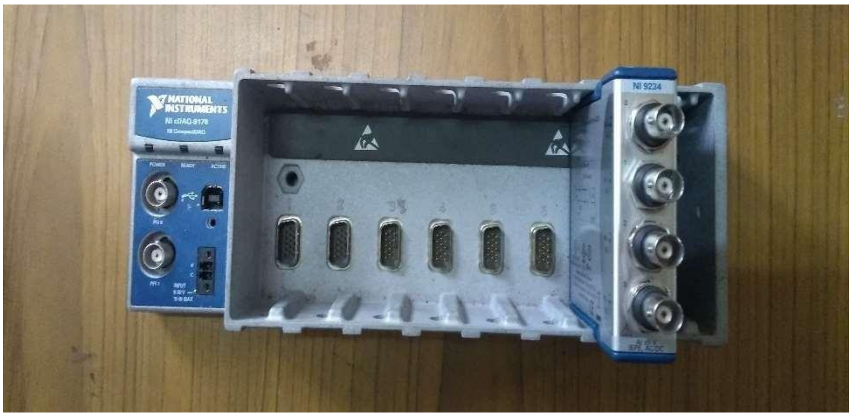
Selection of component for Data Acquisition

a) National Instrument C DAQ-9178

Model	**HT356A15**
Sensitivity	**(±10%) 100 mV/g(10.2 mV/(m/s²))**
Measureme ntRange	**±50 g pk (±490 m/s² pk)**
Electrical Connector	**1/4-28 4-Pin**

The cDAQ-9178 is a Compact DAQ USB chassis designed for small, portable sensor measurement systems. The chassis provides the plug-and-play simplicity of USB to sensor and electrical measurements. It also controls the timing, synchronization, and data transfer between C Series I/O modules and an external host. You can use this chassis with a combination of C Series I/O modules to create a mix of analog I/O, digital I/O, and counter/timer measurements. The cDAQ-9178 also has four 32-bit general-purpose counters/timers.

Input FIFO size	**127 samples per slot**
Timing accuracy	**50 ppm of sample rate**
Output frequency	**0 to 20 MHz**
Timing input frequency	**0 to 20 MHz**
Timing output frequency	**0 to 20 MHz**



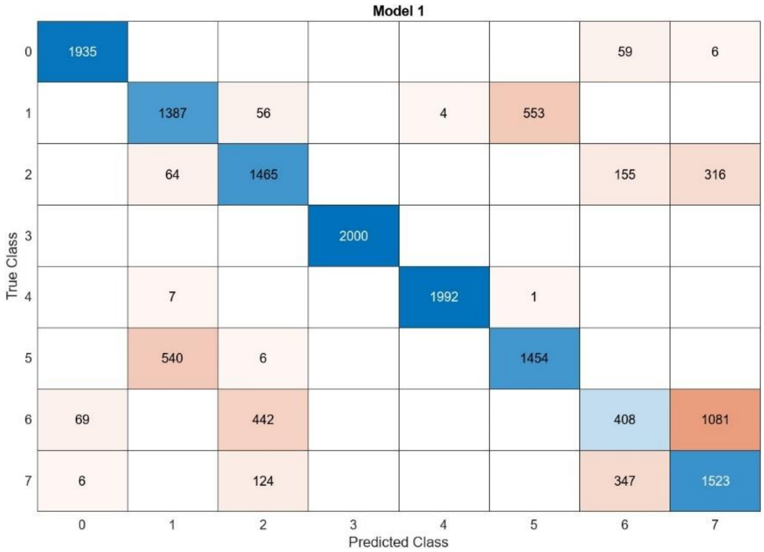
b) **Tri axial Accelerometer sensor**

Triaxial, high sensitivity, ceramic shear ICP® accel., 100 mV/g, titanium hsg, 4-pin conn., high temp electronics to +325 F

DETAILS OF WORK CARRIED OUT

After the selection of each components virtual models were designed and assembled using SOLIDWORKS. Then the test rig was fabricated and assembled as shown in figure above. All the components were assembled on mild steel base plate. Data acquisition involves measuring and recording physical signals, crucial in research and engineering. LabVIEW, a graphical programming language, facilitates this process by creating custom user interfaces, controlling hardware, and analysing data. It supports various hardware devices like NI DAQ boards. In a study on bearing health, vibration data were collected using accelerometers under dry conditions. The data revealed differences in vibration patterns, aiding in identifying potential defects. Accelerometer signals provide valuable information on vibration frequency, amplitude, and direction, crucial for diagnosing sources of vibration. LabVIEW's versatility makes it a go-to tool for data acquisition and analysis in scientific and engineering applications. The study utilized vibration data from rotating machinery to predict its health condition. Features like RMS, skewness, and kurtosis were extracted and classified using SVM algorithms.

Results



Axis

1- healthy

2- 25% tooth cut

3- 50% tooth cut

4- 75% tooth cut

5- 100% tooth cut

6- edge cut

7- edge wear

8- side wear

Conclusion

The information gleaned from the graphical data is condensed and organized into a confusion matrix, a crucial tool for analysing and making sense of the results. This specific matrix corresponds to the Dry run of helical gears, showcasing an accuracy rate of approximately 75%. On the horizontal axis (x-axis) of the matrix, numerical values represent the predicted classes, while on the vertical axis (y-axis), they denote the true classes. Within this matrix, there's a depiction of one class representing healthy gears and seven distinct classes representing various defect conditions. The elements on the diagonal of the matrix signify accurate predictions, indicating instances where the predicted class matches the true class. Conversely, off-diagonal elements highlight instances where misclassifications occurred, revealing discrepancies between predicted and true classes.