Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Experimental investigations on condition monitoring of spur gear using empirical mode decomposition method during dry and wet conditions

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Abstract— Vibration analysis in gearbox condition monitoring is vital for ensuring the dependability, safety, and optimal performance of rotating machinery. Vibration analysis is one of the major techniques in the monitoring of mechanical components. In this study, the vibration data were taken for healthy and defective conditions (dry & wet conditions) using vibration sensors positioned at various locations. These datasets were imported to MATLAB for feature extraction and analysis. The gear fault-related features in the vibration signals are extracted by Empirical Mode Decomposition (EMD). Further, features like RMS, kurtosis, and skewness were extracted. The extracted features were classified in MATLAB classification algorithms like Support Vector Machine (SVM). Amongst different SVM algorithm for Dry condition the most accurate algorithm was medium Gaussian SVM with accuracy of 92.1% and weighted KNN with accuracy of 81.6%. For wet condition most appropriate algorithm were Medium Gaussian SVM with an accuracy of 94.4% and weighted KNN with accuracy of 89%. The confusion matrix plot will be used to distinguish between the classifiers.

Keywords—Empirical Mode Decomposition (EMD), Condition Monitoring, Spur Gear, Intrinsic mode functions (IMFs), MATLAB

1. Introduction

Rotating machine components serve a critical function in the transmission system. The gearbox is an important component of the transmission system that operates under changing load situations and speeds and is prone to wear and tear. It is used in a wide range of industrial applications, including wind power generation, transportation, aircraft, energy, and others. Gears, on the other hand, frequently cause mechanical shutdown and even casualties due to their abrasive operating environment [1]. There are several difficulties that can influence gearbox performance, including gear misalignment, gear wear, overloaded teeth, gear eccentricity, and excessive backlash [2]. There are several ways of detecting and diagnosing defects, including oil debris analysis, vibration analysis, and acoustic emission analysis. Modern approaches like mathematical modeling, model-based decision-making, angular motion analysis, and vibration-based analysis have been the subject of recent research [3-4].

Vibration-based Analysis is a feature analysis technique that is commonly utilized in the condition monitoring of rotating parts. Accelerometers are used to collect vibration signals from both healthy and damaged mechanical components. Mechanical components are a source of information in vibration signals. By processing these, the health state and type of fault can be established.

An appropriate technique for determining the condition of the gearbox is vibration analysis. The Fourier transform was initially the simplest way to analyze the signal because it decomposes the signals into a weighted sum of sinusoids to extract the characteristics, however the FT cannot concurrently give localisation in the time and frequency domains. The empirical mode decomposition (EMD) approach is used to decompose non-stationary and non-linear data. It transforms a signal into a number of intrinsic mode functions (IMFs). The repeating behaviour of the signal is recorded by IMF at a certain time frame. There are several algorithms available to detect and diagnose defects in gearboxes. Support Vector Machine (SVM) is the most widely used algorithm. SVM creates a boundary between two groups. It aims to construct a decision separation between two classes that permits label prediction using one or more feature vectors. The study uses time domain analysis. The dataset was collected from an existing experiment and studied further using MATLAB. RMS, Kurtosis, and skewness are examples of feature extraction.

One of the quick and inexpensive methods for finding gearbox defects is time-domain analysis of vibration data [5-7]. To locate gearbox defects, conventional time domain analysis uses the properties of gearbox vibration signals, such as amplitude and time. Following are the few distinct subgroups for processing the data in time-domain analysis.

RMS Value: The energy content of the vibration profile and, consequently, the vibration's ability to cause damage, are closely correlated with RMS value. When calculating RMS value, wave form time history is also used. RMS value is used to track general noise level and uneven rotating elements. As tooth decay rates grow, RMS value rises. RMS value, in general, can be used to predict the general state of a gearbox. As gearbox wear and pitting progress, vibration levels increase.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$$

where,
n→ number of measurements
x_i→ signal amplitude of nth sample

Kurtosis: Most CMS use it to identify defects in rotating machine components. These symptoms are likely to be caused by a faulty gearbox. A good gearbox has a kurtosis of about 3 degrees.

$$Kutosis = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{y_i - \bar{y}}{\alpha}\right]^4 - 3$$

where,
y_i → raw time series at point n
$\bar{y}$→mean of the data
σ → SD of the collected data
n → number of data points collected

Skewness: It is a measure of a distribution's asymmetry. When the left and right sides of a distribution are not mirror images, it is said to be asymmetric. The skewness of a distribution might be right (or positive), left (or negative), or zero. The main objective of this work is to detect a fault, or a degradation process of a spur gear, that has reached a certain symptomatic level and to provide an indication of the abnormality in time before the functional breakdown occurs.

2. Objectives

The main objectives of this study to identify faults or degradation processes that have progressed to a particular symptomatic level and to provide an early warning of irregularity before a functional breakdown occurs. A thorough examination of the procedures are followed for checking the condition of the gearbox to increase safety, minimize maintenance costs, and run as much as possible between long shutdowns this is done by gathering a significant volume of sensor data.

3. Methodology

The experimental setup consists of a spur gear with a 1:2 gear ratio placed on a 20 mm diameter EN-24 shaft. Pinion is coupled to a 1 HP single phase motor by a flange coupling. The tri-axial accelerometer sensor is used to collect vibration data from the experimental setup, which was made up of eight healthy and four unhealthy scenarios. This accelerometer sensor is linked to NIDAQ. The pillow block bearing is equipped with an accelerometer sensor. The detailed specifications of gear and pinion are shown in the TABLE I.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

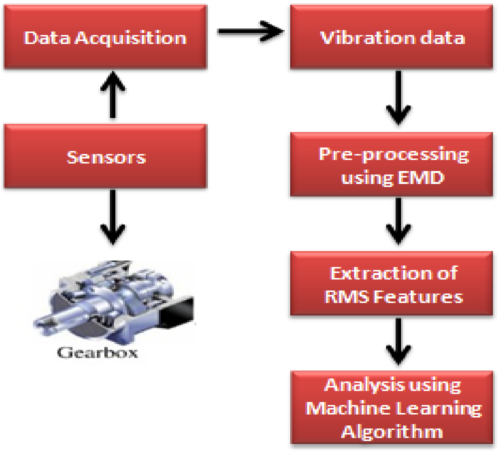

Fig.1. Methodology in vibration analysis

TABLE I: GEAR AND PINION SPECIFICATIONS

Pinion	19 teeth
Gear	38 teeth
Module	2
Material	Cast iron (for pinion) EN-8 (for gear)
Gear ratio	1:2

Fig2. Test-rig Dry condition

Fig.3. Test-rig wet condition

Gear Transmission oil was used for lubrication purposes to ensure smoother performance. The oil used for lubrication is MICO Tqf (ATF type A oil), and its viscosity is 8.5 centistokes (cSt) at 40°C which operates between the temperature of -30°C to 120°C

A. Data Acquisition

Data acquisition is the process of measuring and recording physical or electrical signals from the environment. It is a crucial step in scientific research and engineering applications, as it allows researchers to collect and analyze data in real-time. LabVIEW programs are known as Virtual Instruments (VIs), which consist of graphical blocks that can be connected to create complex applications. These VIs can be customized to fit specific data acquisition needs. The software supports a wide range of hardware devices, including National Instruments (NI) DAQ boards, Compact RIO controllers, and PXI systems. The LabVIEW code can be used to interface with these devices, control their settings, and acquire data in real-time.

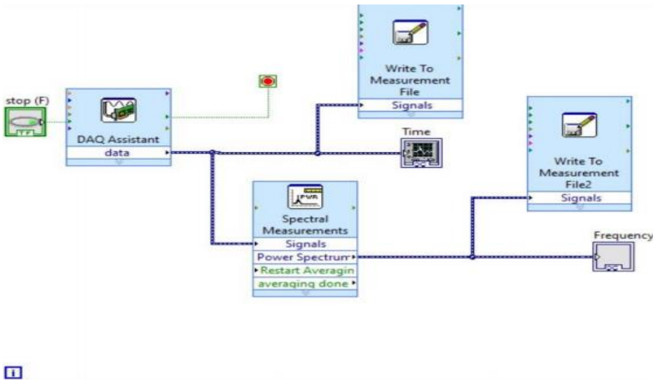

Fig.4. Data Acquisition for dry condition

Vibration data for dry condition were collected using triaxial accelerometer which was interfaced to Data Acquisition System (National instruments). The accelerometer was fixed on outer casing of pillow block bearing. Initially, data were extracted for healthy condition. Data were acquired in steady state for 10 minutes. Similar procedures were followed for other seven defects.

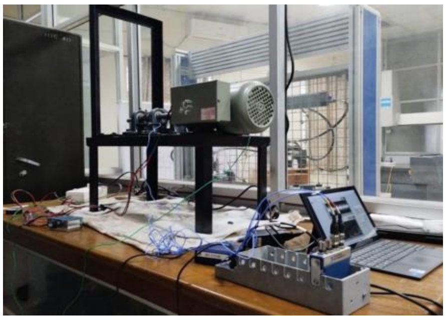

Fig. 5. Data Acquisition for Dry condition

B. Data Acquisition for wet condition

Similarly, vibration data were collected for wet condition where two meshing gears dipped in lubricating oil. Casing was made by using an acrylic sheet and a ball bearing. When an object vibrates, it produces a corresponding acceleration that can be detected by an accelerometer sensor. The signal acquired from an accelerometer sensor for vibration analysis typically includes information about the frequency, amplitude, and direction of the vibration. This information can be used to identify the source of the vibration.

Fig.6. Data Acquisition for Wet condition

4. Selection of IMF for acquired data (Pre-Processing)

IMFs, or intrinsic mode functions, are a collection of functions created by breaking down complicated signals into their simpler and more significant parts. When analysing vibration data, choosing the right IMFs is essential for correctly capturing a structure's dynamic behaviour. The relative energy criteria, which compares each IMF's energy distribution to the signal's total energy, is one way for choosing IMFs. The IMFs with the most meaningful and instructive vibration modes are those that meet this requirement. The relative energy criterion involves calculating the energy of each IMF by squaring the values of the signal and integrating over the entire time range. A proportion of the overall signal energy is then used to represent how much energy each IMF contributes. The selection of IMFs for further analysis is made based on the assumption that IMFs with higher energy content compared to the overall signal energy include more important vibration modes. Below are the figures (Fig.7-18) which represents the IMFs for different conditions.

A. IMFs for Dry Condition

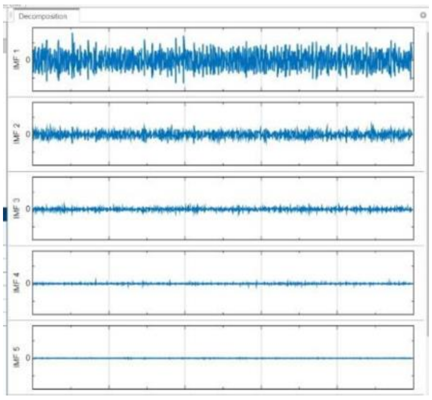

Fig.7. IMF for Healthy condition

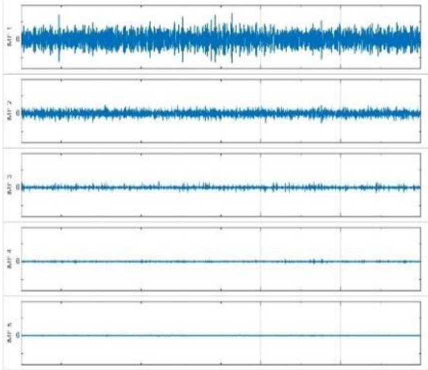

Fig.8. IMF for 25% Tooth cut

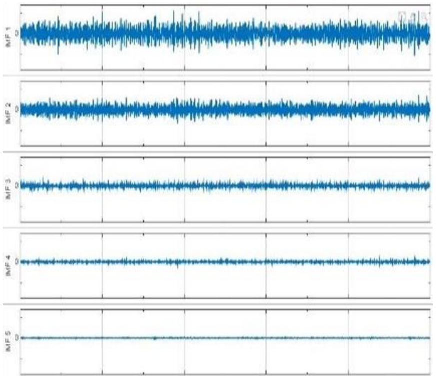

Fig.9. IMF for 50% Tooth cut

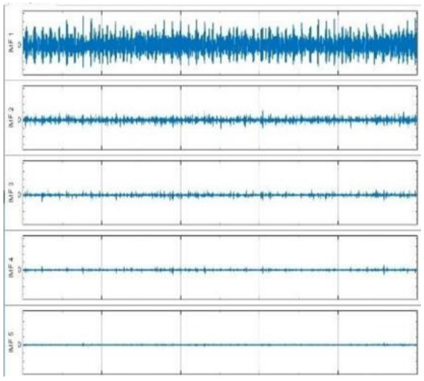

Fig.10. IMF for 75% Tooth cut

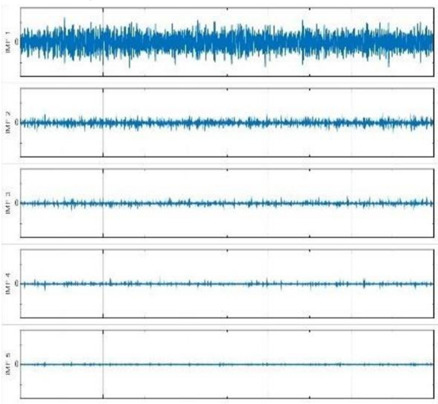

Fig.11. IMF for 100% Tooth cut

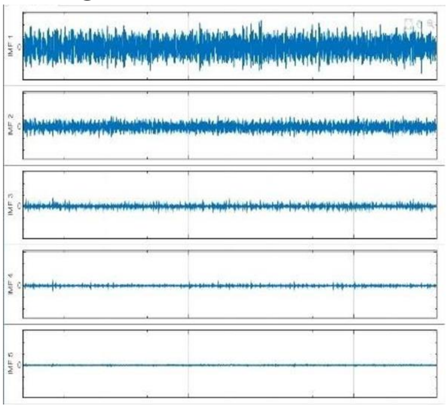

Fig.12. IMF for 25% Edge cut

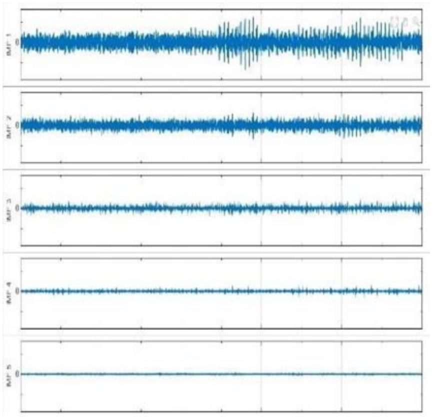

Fig.13. IMF for 50% Edge cut

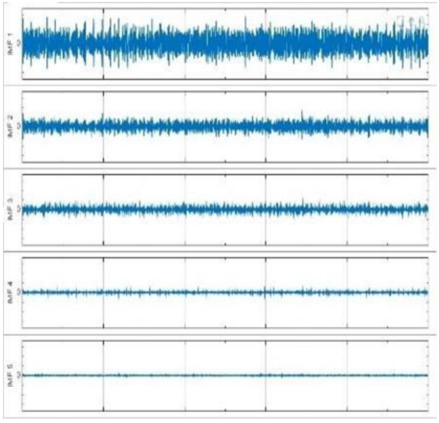

Fig.14. IMF for Edge Wear

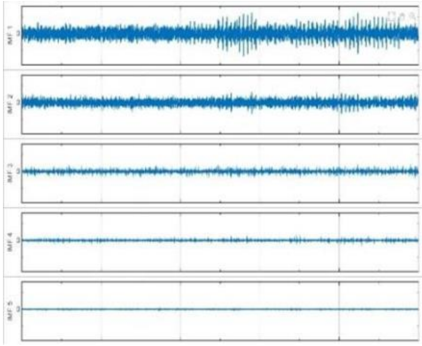

Fig.15. IMF for Edge wear Along face width

B. IMFs for Wet Condition

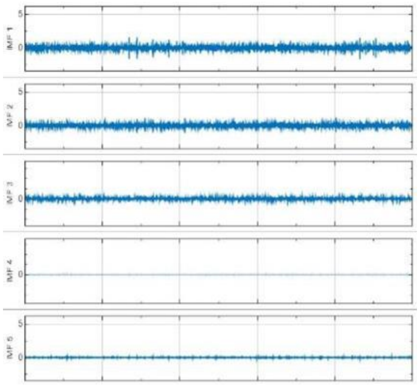

Fig.16. IMF for healthy(w)

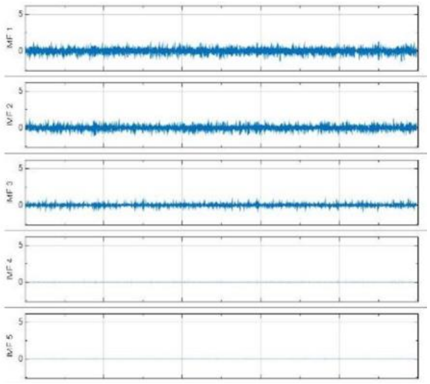

Fig.17. IMF for 50% Tooth cut(w)

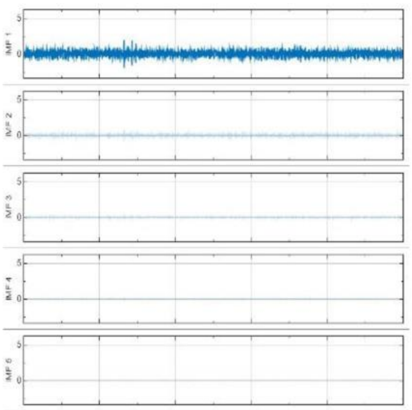

Fig.18. IMF for 100% Tooth cut (w)

5. Feature extraction from selected IMF

Condition monitoring is the technique of evaluating a system or machine's performance and health to find any possible flaws or problems before they become serious. It is crucial to choose features that are capable of capturing critical data on a system's activity in order to monitor its state efficiently. To extract these features code was written in MATLAB. Following Figures from Fig. 19-24 shows the graphical representation of above-mentioned features for all condition of gears.

A. RMS plot for dry condition

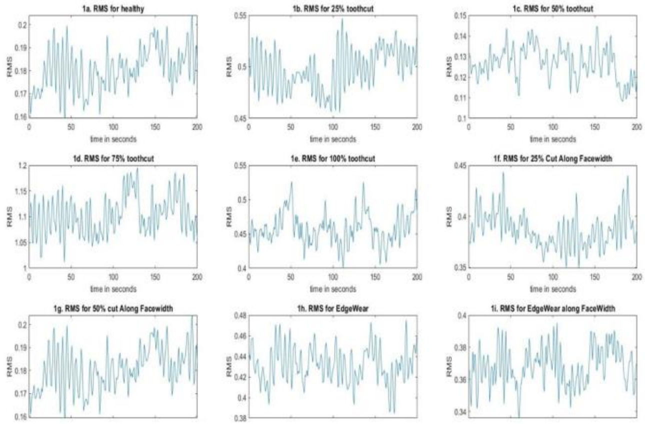

Fig.19. RMS Plot for different gear condition

B. RMS plot for wet condition

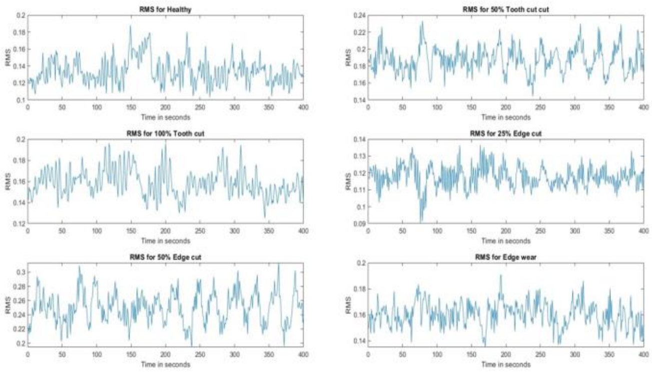

Fig.20.RMS plot for different gear condition

C. Skewness plot for dry condition

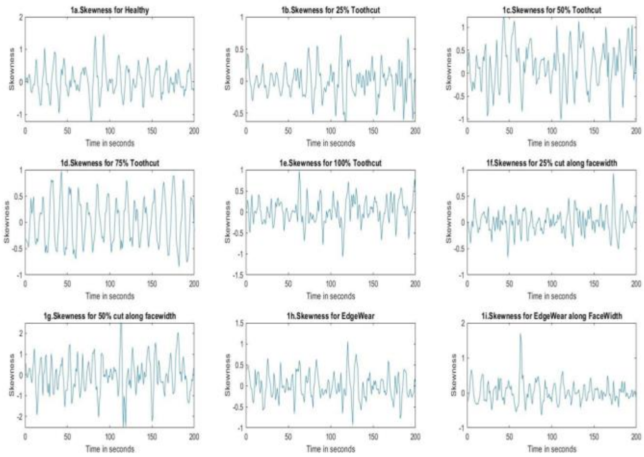

Fig.21. Skewness plot for different gear condition

D. **Skewness** ***plot for wet condition***

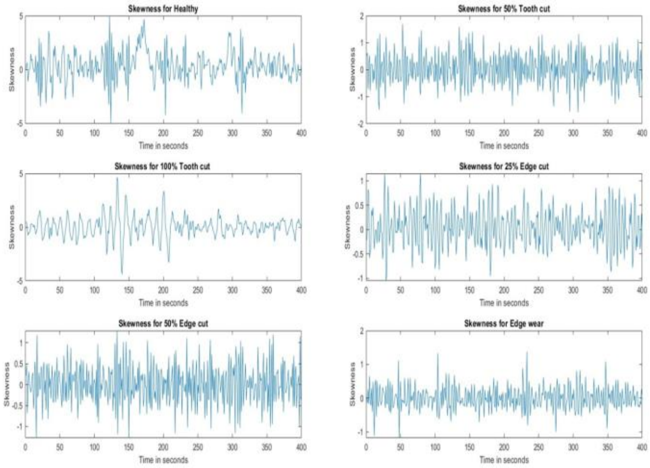

Fig.22. Skewness plot for different gear condition

E. Kurtosis plot condition for dry

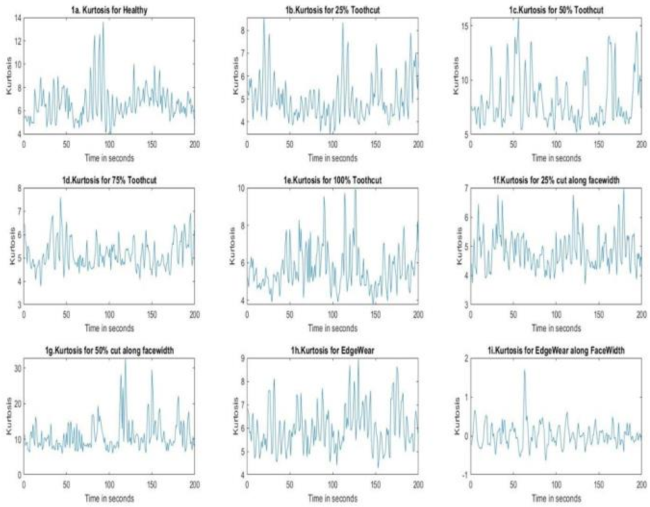

Fig.23: Kurtosis plot for different gear condition

F. Kurtosis plot for wet condition

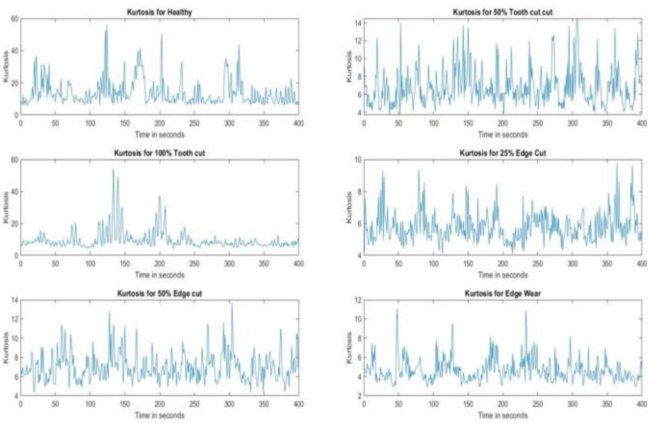

Fig.24: Kurtosis plot for different gear condition

6. Result and Discussion

After the extraction of features, they were imported into classification learner app in MATLAB to predict the accuracy using advanced signal process SVM-based classification learner to differentiate between normal and faulty conditions. The SVM-based classification learner was developed to differentiate between normal and faulty conditions. The accuracy of the SVM data for both wet and Dry conditions are given in TABLE II. The SVM algorithm was trained using the extracted features which provide good accuracy even with a small amount of training data. SVM can handle non-linear data, and the accuracy of the algorithm was evaluated using a confusion matrix, which makes it well-suited for gear fault diagnosis, where the signals can be complex and non-linear.

TABLE II ACCURACY OF SVM ALGORITHM FOR DRY & WET CONDITION

SI No	Algorithm	Accuracy (%) (Dry)	Accuracy(%) (Wet)
1	Linear SVM	91.6	93.8
2	Quadratic SVM	92	94.3
3	Fine Gaussian SVM	85.9	92.9
4	Cubic SVM	90.8	93.6
5	Medium Gaussian SVM	92.1	94.4
6	Course Gaussian SVM	91.0	92.9

is Medium Gaussian SVM with an accuracy of 94.4%. Linear SVM and Fine Gaussian SVM also have high accuracy rates, Cubic SVM and Medium Gaussian SVM have accuracy The most accurate SVM algorithm, with an accuracy of 92.1%, is the Medium Gaussian SVM. This approach generates a hyperplane that divides the data into various classes using a medium bandwidth Gaussian kernel function.

While having a similar accuracy rate to the Medium Gaussian SVM, Linear SVM and Quadratic SVM may be unable to handle more complicated datasets because to their simplicity. With a lower accuracy rate of 85.9%, Fine Gaussian SVM may not be as successful in precisely separating the data into hyperplanes due to its Gaussian kernel function's limited bandwidth. Although Cubic SVM and Course Gaussian SVM also offer excellent accuracy rates, they can be overly complicated for some applications, which would result in slower processing and more expensive calculation. Overall, it can be interpreted that the Medium Gaussian SVM strikes a reasonable compromise between accuracy and complexity and might be a solid option for many classification problems.

Based on the accuracy percentages provided in the updated SI list, the best performing SVM algorithm rates slightly lower than Quadratic SVM, but they may still be good choices depending on the specific requirements of the task at hand. It is important to note that the choice of algorithm ultimately depends on the specific requirements of the task at hand and the characteristics of the dataset being analyzed. Factors such as the size and complexity of the dataset, the number of features, and the balance of the classes being classified can all impact the performance of different SVM algorithms.

The accuracy of the KNN algorithm were also compared for both wet and dry conditions and illustrated in TABLE III.

TABLE III: ACCURACY OF KNN ALGORITHM FOR DRY & WET CONDITION

Sl. No.	Algorithm	Accuracy (%) (Dry)	Accuracy(%) (Wet)
1	**Fine KNN**	77.7	86.3
2	**Medium KNN**	78.1	88.9
3	**Cubic KNN**	78.3	88.7
4	**Cosine**	69.1	85.2
5	**Weighted KNN**	81.6	89

It can be observed that Weighted KNN has got accuracy of 81.6% and cosine KNN has got least accuracy of 69.1%.For wet condition, Weighted KNN has got accuracy of 89% which is higher than the accuracy of weighted KNN for dry condition.

Confusion Matrix

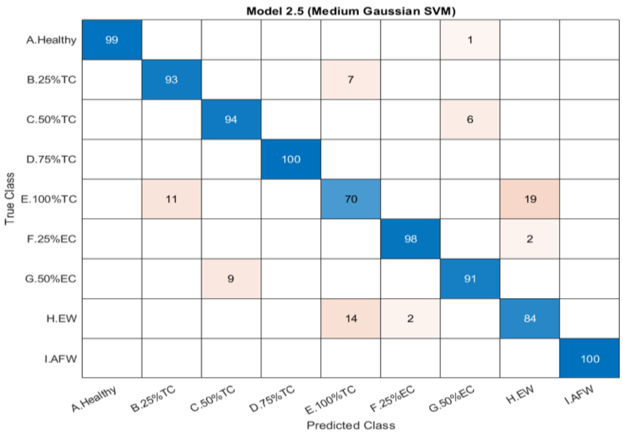

Fig.25: Confusion Matrix of SVM for dry condition

According to the confusion matrix (Fig. 25), the classification accuracy obtained for the dry conditions using the machine learning approach was 92.1%. The program received a total of 100 samples of data from each condition. From Fig. 26, it is evident that 99 out of 100 data points seemed accurately detected, whereas 1 data point was mis labeled as a 50% Edge cut. All 100 data were appropriately categorized for 75% Tooth cut and Wear along face width. Only 70 data for 100% tooth cut were accurately categorized; 11 data were categorized as 25% tooth cut, and 19 data were categorized as edge wear. These results supported earlier research on spur gear defect detection that was done [8–10]. The confusion matrix (Fig. 26) illustrates the 94.8% classification accuracy for the wet circumstances that was achieved using the machine learning method. The algorithm received 400 sample sets of data total from each condition as input From Fig. 26, it can be seen that out of 400 data points, 367 data were classified correctly and 33 data were classified as 100% tooth section from the good condition and were classified incorrectly. In the “50% tooth loss” condition, 394 data points were correctly classified and 6 data points were incorrectly classified as “healthy”. At 100% tooth cut, 345 data points were correctly classified, 26 data were incorrectly classified as healthy, and 29 data were incorrectly classified as edge-wear. 400 data points are accurately categorized using an edge cut of 25%. 399 data points for 50% edge cutting were accurately identified, whereas 1 data point was misidentified as edge wear. When it comes to edge wear, 40 out of 360 data points are appropriately characterized as 100% tooth cut.

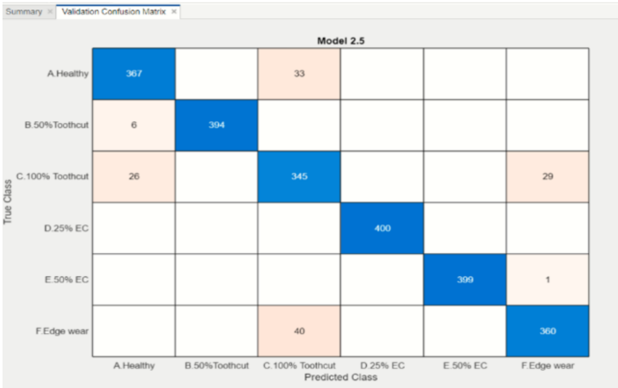

Fig.26: Confusion matrix of SVM for wet condition

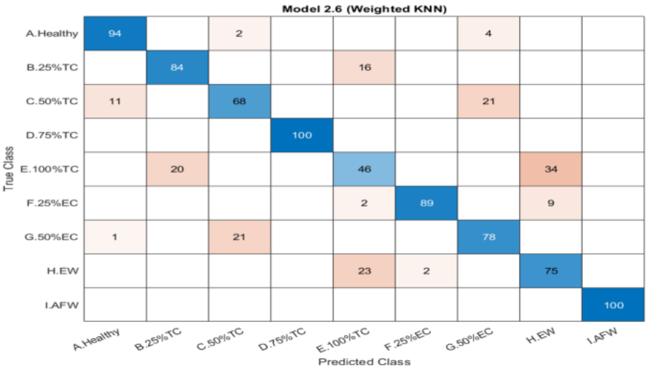

Fig. 27: Confusion Matrix of KNN for dry condition

According to the confusion matrix (Fig. 27), the classification accuracy for the dry conditions using the KNN machine learning method was 81.6%. The algorithm received as input a total of 100 sample records from each condition. From Fig. 27, out of 100 data points, 94 were classified correctly, while 6 data points from the good condition were misclassified. 80 data points were successfully classified under the 25% TC condition, while 20 data points were misclassified. Additionally, the confusion matrix was used to classify and present the remaining issues. Using the ANN technique, the created dataset is used to extract the useful feature.

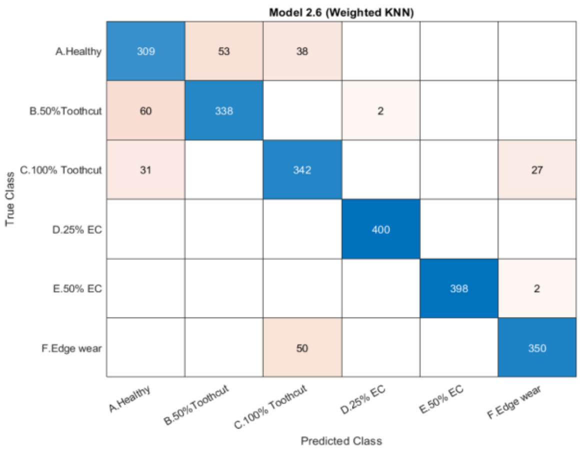

Fig.28: Confusion matrix of KNN for wet condition

According to the confusion matrix (Fig. 28), the classification accuracy for the wet conditions using the machine learning algorithm KNN was 89.0%. The algorithm received as input a total of 400 sample data sets from each condition. According to Figure 28, out of 400 data points, 309 were correctly identified while 53 were misclassified.

7. Conclusion

The different features like skewness, kurtosis and RMS were extracted from selected intrinsic mode functions (IMFs) from EMD. The accuracy of the dataset for a healthy chipped tooth and worn tooth condition were analyzed using SVM. It was found that for this given dataset, the accuracy using Fine Gaussian SVM algorithms was better than other SVM algorithms for all three different conditions. For the experimentation, a similar methodology was adapted where data were acquired using LabVIEW and imported to MATLAB. Amongst different SVM algorithm for Dry condition the most accurate algorithm was Medium Gaussian SVM with accuracy of 92.1% and weighted KNN with accuracy of 81.6%. For wet condition most appropriate algorithm were Medium Gaussian SVM with an accuracy of 94.4% and weighted KNN with accuracy of 89%. The accuracy of SVM & KNN algorithms can be influenced by different factors such as size and complexity of the dataset, the number of features, and the balance of the classes being classified can impact the performance. A high accuracy indicates that the SVM model is performing well in accurately predicting the condition of the gear box. It suggests that the model can be used effectively to differentiate between normal and faulty gear boxes. On the other hand, a low accuracy suggests that the model may have difficulty distinguishing between different gear box conditions, leading to misclassifications.

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