Indian Journal of Science and Technology, Vol 9(33), DOI: 10.17485/ijst/2016/v9i33/101341, September 2016
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Fault Diagnosis of Helical Gearbox Using Vibration Signals through K-Star Algorithm and Wavelet Features

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Abstract

Objectives: Gears are machine elements that transmit motion by successively engaging teeth. In technical terms, gears are used to transmit motion. Fault in gears can lead to major problems which may end up in affecting the gear's functionality. Hence, fault diagnosis at an initial stage is of utmost importance to reduce losses that might occur. Continuous monitoring of the gears is very necessary. Vibration signals recorded for good and faulty conditions are used for fault detection in the helical gearbox. The fault diagnosis is done using feature extraction, feature selection and feature classification. Firstly, feature extraction was carried out using MATLAB software. Feature selection was done using J48 classifier. The classification accuracies for different conditions were calculated and compared by using K-Star classifier and the results obtained were very promising**. Methods/Analysis**: Vibration signals were obtained from the experimental set up of the helical gearbox. The recorded signals were then used for feature extraction using MATLAB through different wavelet features. The total number of signals extracted was 448 with each class consisting of 64 signals. The families of wavelets taken into account for fault diagnosis were Haar, Discrete Mayer, Daubechies, Biorthogonal, Reverse Biorthogonal, Coiflet and Symlets. In wavelet selection, signals were split into different frequency components and each component was studied with a resolution matched to its scale. J48 classifier was used to carry out the feature selection process and decision tree was obtained for Sym 8 wavelet. The best combination of nodes was visualized and further feature classification was done on these nodes. By varying the global blends the optimum number of objects was selected to obtain the highest classification accuracy. **Finding**: The classification accuracy for the built model was 91.74%. The data extracted from the vibration signal is used for the classification purpose. This maximum classification accuracy was obtained with K star algorithm. **Novelty/ Improvements**: Wavelet selection was different from Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. K Star algorithm was used to carry out the fault diagnosis.

Keywords: Decision Tree, Gearbox Fault Diagnosis, J48 Classifier, K-Star Classifier, Wavelet

1. Introduction

Helical gearbox condition monitoring[1] has gained importance in the past few years, evident in the work done in. A significant number of failures occur due to localized defects. Fatigue cracking occurs due to constant cyclic contact stressing, when a major portion of the surface is displaced during operation, leading to localized defects at an initial stage. Helical gearbox operates under numerous speeds and loads hence, it is difficult to measure and delineate local defects. Nowadays, physical variables such as vibration[2] and acoustic signals are used for fault detection and diagnosis[3]. The traditional pattern recognition includes a very large collection of different types of mathematical tools (preprocessing, extraction of features and final recognition). Fault classification techniques have been used in a wide range of pattern recognition

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applications including sound vibration monitoring. In the paper presented in, the author has carried out model study with the detection of different mechanical faults under a wide range of working conditions of speed and load[4]. The testing conditions for the test bench are similar to other machinery like turbines. Although the working conditions are restricted, the information obtained, aids in faster fault detection and better prognostication.

Vibration signals extracted from rotating parts of machineries carries a lot of information within them about the condition of the operating machine[5,6]. Further processing of these raw vibration signals measured at a convenient location of the machine unravels the condition of the component or assembly under study. Wavelet analysis[7,8], being a popular time frequency analysis method has been applied in various fields to analyze a wide range of signals covering biological signals, vibration signals, acoustic and ultrasonic signals, etc. With the capability to provide both time and frequency domain information, wavelet analysis is used mainly for time-frequency analysis of signals, signal compression, signal de-noising, singularity analysis and features extraction. The main challenge in using wavelet transform is to select the most optimum mother wavelet for the given tasks, as different mother wavelet is applied on to the same signal, it may produces different results. The paper presented in reviews on the mother wavelet selection methods[9] with particular emphasis on the quantitative approaches. The wavelet tool, analyzed from a theoretical standpoint can help obtain a family of basic functions of signals, illustrated in time and frequency formats. Various mother wavelets have been studied in this paper. The research done in experimented on the various mother wavelets, Haar, Daubechies, coiflet, symlet wavelets for fault detection[10]. Various mother wavelets were studied using numerous fault resistance values. Using Discrete Wavelet Transform (DWT) contrasts were drawn with the help of in Multi Resolution Signal Decomposition (MSD). The most suitable wavelet proposed was coiflet wavelet, due to minimum sum of fault resistance coefficients. However, in this study, SYM wavelets were clearly the better option due to higher accuracy.

In deal with the effectiveness of wavelet-based features for fault diagnosis of a gearbox using Artificial Neural Network[11] (ANN) and Proximal Support Vector Machines[12]. The principal features obtained from classification of Morlet wavelet using J48 algorithm served as input for ANN and PVSM. Comparisons of classification efficiency of faults in the bevel gearbox were made. Both ANN and PVSM had a high average classification efficiency of 97.5% and 97% respectively. But, PVSM had an edge over ANN due to lesser time required for training. A similar concept is used in this paper, but the analysis here was done on a helical gearbox. The concept of using vibration was initially used in the paper in, where vibration signals were used to detect faults and measure the severity[13]. In attempted to diagnose severity of faults in ball bearings using various machine learning techniques[14], like Support Vector Machine (SVM) and Artificial Neural Network (ANN). This work attempts to classify faults of different severity level in each bearing component which is not considered in most of the previous studies. Classification efficiency achieved by proposed methodology is compared to the other methodologies available. The classification accuracy of SVM and ANN with selected features is reported as 100% for AF1, but for AF2 and AF3, ANN has a lower classification accuracy than SVM. Also, for both of the cases, AF2 and AF3, superior precision rates of SVM are achieved than ANN. This is due to the reason of better generalization capability of SVM. The study presents a novel method of multiclass fault classification in various bearing components. Defects with multi fault severity levels in various bearing components such as inner race, outer race and rolling element were considered. Decision trees are an essential feature of the fault diagnosis process. The research done on decision trees in. describes about statistical features extracted from vibration signals and the important ones were selected using decision tree[15] (dimensionality reduction). The decision tree has been formulated using J48 algorithm. The selected features were then used for classification using Bayes classifiers[16] namely, Naïve Bayes and Bayes Net. The paper also discusses the effect of various parameters on classification accuracy. The J48 algorithm concept is used in this paper to conduct feature selection. A similar approach[17] was attempted in. A vibration-based condition monitoring system is presented for the helical gearbox as it plays a relatively critical role in most of the industries. Naïve Bayes algorithm and Bayes Net algorithm was used for feature classification in the paper, which provided classification accuracy of 83.37% and 81.77% respectively, for fault diagnosis through statistical features extracted from the vibration signals of good and faulty components of the helical gearbox. However in this paper, K-Star algorithm is used for feature classification which resulted in a higher classification accuracy, hence proving to be more efficient.

In explain the application of the three steps[18] mentioned. They are carried out by the software Weka[19,20], where various parameters are varied to obtain the accuracies, which are used to study the faults at different load conditions on the gears. The previously established set of classes was used as a guideline to classify items according to the features. The paper presented in puts light on performance evaluation[21] based on the correct and incorrect instances of data classification using Naïve Bayes and J48 classification algorithm. Naive Bayes algorithm is based on probability and J48 algorithm is based on decision tree. The classifiers are evaluated on the basis of bank dataset. Importance is given for increasing and reducing true and false positive rates respectively, in expense for high classification accuracy. The experiments results shown in the paper are about classification accuracy, sensitivity and specificity. The best fit tree is selected from the J48 classifier to carry out further analysis. The statement can be bolstered[22] by the paper in. Decision tree is a popular technique for supervised classification, especially when the results are interpreted by human. Multivariate[23] decision tree uses the concept of attributes correlation and provides the best way to perform conditional tests as compare to univariate approach, as mentioned in the paper. The research study concludes that multivariate decision tree approach is far better than univariate approach while it allow us dealing with large amount of data The present study uses the K-Star algorithm for finding out the accuracies of the wavelets. The K-Star classifier is a highly reliable and efficient classifier. The functional aspects[24] of the classifier have been explained in the paper in. Their results show a significant increase in accuracy and decrease in learning time, hence emphasizing that K-Star algorithm is a convenient and effective methodology which can be used for fault detection. This paper uses vibration signals to conduct the fault diagnosis. Feature extraction was done using discrete wavelet features. Feature selection[25] was carried out by J48 algorithm, the decision tree enables the visualization of the contribution of features for fault diagnosis. Finally feature classification is done with K-Star classifier, the results obtained were highly accurate than previous research[26],In conducted using vibration signals for fault analysis.

2. Materials and Methods

The test rig setup was constructed to study fault diagnosis of helical gearbox. The details about the experimental setup and experimental procedure are discussed in the following subsection.

The experimental setup is shown in Figure 1. The setup consists of 5 HP two stage helical gearbox. The gearbox is driven by a 5.5 HP, 3-phase induction motor with a speed of 1440 RPM. For the present study, the motor operates at 80 RPM. The speed of the motor is controlled by an inverter drive. With a step up ratio of 1:15, the speed of the pinion shaft in the second stage of gearbox is 1200 RPM. The summary of specification of test rig is given in Table 1.

The pinion is connected to a DC motor to generate 2 KW power, hence, is dissipated in a resistor bank. Therefore, the actual load on the gearbox is only 2.6 HP which is 52% of its rated power 5 HP. Utilization of load in industrial environment varies from 50% to 100%. The resistor bank helps minimize the torsional vibrations occurring due to the torque fluctuations and tyre couplings restrict gear backlash. The motor, gearbox and

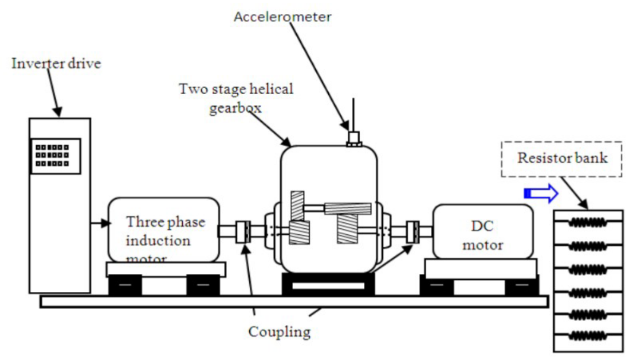

Figure 1. Experimental setup.

Table 1. Specifications of Helical gearbox

	First stage	Second stage
Number of teeth	44/13	73/16
Pitch circle diameter (mm)	198 /65	202 /48
Pressure angle (°)	20	20
Helix angle	20	15
Modules	4.5/ 5	2.75 / 3
Speed of shafts	80 rpm (input)	1200 rpm (output)
Mesh frequency	59 Hz	320 Hz
Step - up ratio	1:15	
Rated power	5 HP	
Power Transmitted	2.6 HP	

generator are mounted on I-beams, which are anchored to a massive foundation. A sampling frequency of 8.2 kHz, was maintained with regard to the NY Quist sampling theorem. The length of sample signal is 8192 (2^{13}). Total number of sample signals are 448 and each class consists of 64 sample signals.

The signals were recorded by using accelerometers. The recorded signals were then used for feature extraction using MATLAB through different wavelet features. The extracted features were then classified using decision tree classifier. The flowchart of methodology followed is shown in Figure 2.

2.1 Feature Extraction

At each level, the detail coefficient was used to compute the energy content using the following formula:

$$Vi = \sum_{i=1}^{n} Xi^{\wedge}2$$

Where $x_{i\,=}$ details coefficients n = number of detail coefficients. Then the features were defined as the energy content at each level. The feature vector is defined as:

V = (v1, v2, v3,.. vm)

Where m-(number such that length of signal = 2^m*v1, v2, v3* are energy content at given level.

Families of wavelets taken into account for the fault diagnosis are:

- Haar wavelet.
- Discrete Meyer wavelet.
- Daubechies[27] wavelet – Db1,db2, db3, db4, db5, db6, db7, db8, db9, db10.

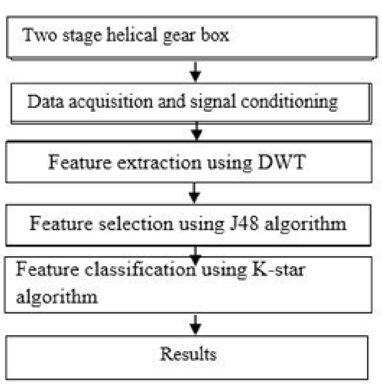

Figure 2. Flowchart of methodology followed.

- Biorthogonal wavelet – bior1.1, bior 1.3, bior 1.5, bior 2.2, bior 2.4, bior 2.6, bior 2.8, bior 3.1, bior 3.3, bior 3.5,bior 3.7, bior 3.9, bior 4.4, bior 5.5, bior 6.8.
- Reversed Biorthogonal wavelet - rbio1.1, rbio 1.3, rbio 1.5, rbio 2.2, rbio 2.4, rbio 2.6, rbio 2.8, rbio 3.1, rbio 3.3, rbio 3.5, rbio 3.7, rbio 3.9, rbio 4.4, rbio 5.5, rbio 6.8.
- Coiflet – coif 1, coif 2, coif 3, coif 4, coif 5.
- Symlets – sym 2, sym 3, sym 4, sym 5, sym 6, sym7, sym 8.

2.2 Wavelet Selection

Wavelets are mathematical function that splits data into different frequency components and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes**.** Wavelet algorithms process data at different scales or resolutions. The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet. Fifty four distinct wavelets[28] were selected by using mother wavelet selection technique. The classification accuracy for BIOR, COIFLET, DB, DMEY and HAAR and RBIO wavelets has been found as shown in Figures 3 to Figure 7 respectively. Wavelet data from sym 2, sym 3, sym 4, sym 5, sym 6, sym 7 and sym 8 were studied and a comparative analysis was carried out using J48 algorithm. Sym 8 was selected based on the highest accuracy obtained as shown is Figure 8.

2.3 Feature Selection

J48 algorithm was used to carry out the feature selection process. It creates a binary tree. A decision tree is formulated to carry out the classification process. This tree is applied to each tuple[29] in the database and results in

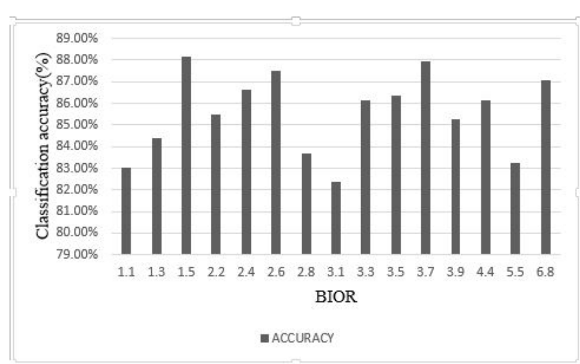

Figure 3. BIOR wavelet versus classification accuracy.

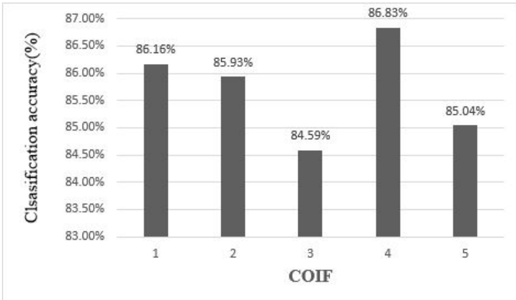

Figure 4. COIFLET wavelet versus classification accuracy.

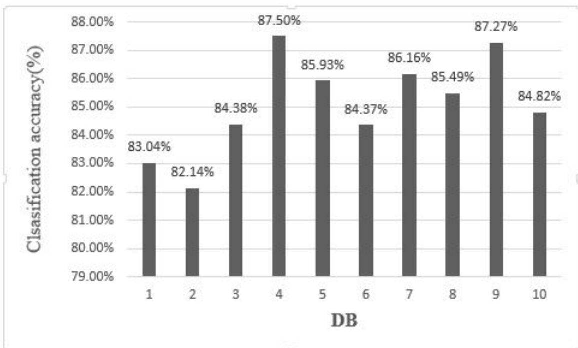

Figure 5. DB wavelet versus classification accuracy.

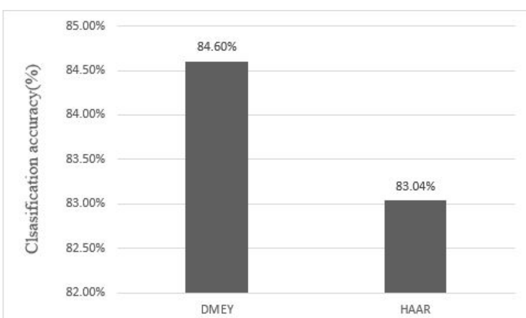

Figure 6. DMEY and HAAR versus classification accuracy.

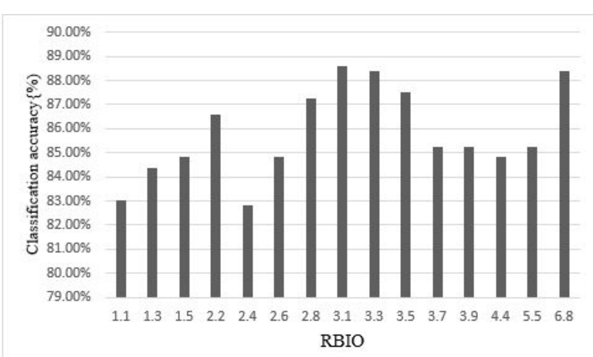

Figure 7. RBIO wavelet versus classification accuracy.

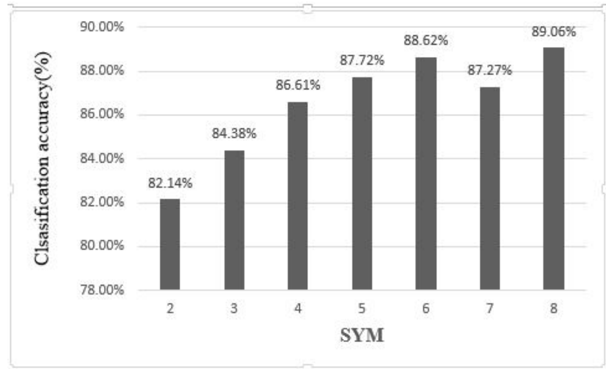

Figure 8. SYM wavelet versus classification accuracy.

classification are similar to the work done in. A decision tree is used to learn a classification[30] function which concludes the value of a dependent attribute (variable) given the values of the independent (input) attributes (variables). It includes the technology of research large and complex bulk of data in order to discover useful patterns. This idea is very important as it enables modeling and knowledge extraction from the bulk of data available.

SYM 8 wavelet data was used and classification was carried out by using J48 tree algorithm. Hence, decision tree was obtained through visualization of decision tree. V3 is the top node, followed by the combination of node s,v3+v10,v3+v10+v1,v3+v10+v1+v6,v3+v10+v1+v6+v5, v3+v10+v1+v6+v5+v4,v3+v10+v1+v6+v5+v4+v2, v3+v10+v1+v6+v5+v4+v2+v7,v3+v10+v1+v6+v5+v4+v2+v7+v8, v3+v10+v1+v6+v5+v4+v2+v7+v8+v9, v3+v10+v1+v6+v5+v4+v2+v7+v8+v9+v11, v3+v10+v1+v6+v5+v4+v2+v7+v8+v9+v11+v12, v3 +v10+v1+v6+v5+v4+v2+v7+v8+v9+v11+v12+v13.

Feature selection was done for all 13 symlets using the J48 classifier. As mentioned SYM 8 was selected based on the accuracy it produced. The decision tree visualized the nodes of the SYM 8 wavelet, as presented in Figure 9. Further tests took place using the J48 algorithm to identify the sequence of nodes and the node with the best accuracy. The nodes, v3+v10+v1+v6+v5+v4+v2 had an accuracy of 89.2857 *i.e.* the maximum, among the 13 combinations. The Figure 10 shown compares the accuracies obtained by the different combination of nodes and helps identify the node with the highest accuracy.

2.4 Feature Classification

K-Star is an instance-based classifier. The class of a test instance is based on the training instances similar to it,

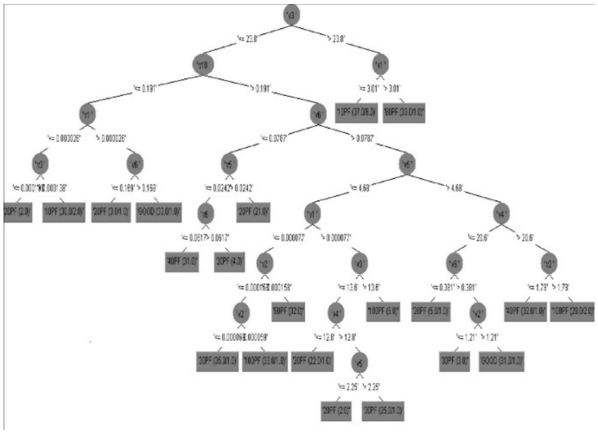

Figure 9. J48 decision tree.

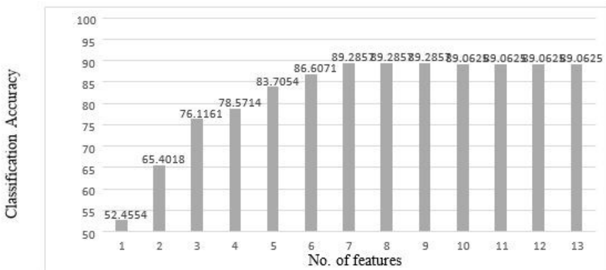

Figure 10. Accuracy versus SYM nodes.

as determined by some similarity function. It differs from other instance based learners in that it uses an entropy-based distance function. Instance-based learners classify an instance by comparing it to a database of pre-classified examples. The K-Star algorithm uses entropic measure, based on probability of transforming an instance into another by randomly choosing between all possible transformations. A uniform method of management of real valued, symbolic and missing value attributes is obtained.

The K-Star function can be calculated:

K* (yi , x) = –ln P*(yi, x)

Where P* is the probability of all transformational paths from instance x to y. The path of x to arrive at y occurs in a random manner. It will be performed optimization over the percent blending ratio parameter. In the metric used for evaluating of our proposed architecture the following terms have been used: True Positive (TP) for correctly identified, True Negative (TN) for correctly rejected, and False Positive (FP) for incorrectly identified, Precision, Recall, F-Measure and Accuracy. Achieving very high accuracy is very easy by carefully selecting the sample size but if we use accuracy as a measure for testing the performance of the system, the system can be biased and can attain very high accuracy. However, precision and recall are not dependent on the size of the training and the test samples. These metrics are derived from a basic data structure known as the confusion matrix.

$$Precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp + fn}$$

Recall in this context is also referred to as the True Positive Rate or Sensitivity and precision is also referred to as Positive Predictive Value (PPV); other related measures used in classification include True Negative Rate and Accuracy. True Negative Rate is also called Specificity.

Accuracy is the most basic measure of the performance of a learning method. This measure determines the percentage of correctly classified instances. From the confusion matrix, we can

state that:

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

F-measure is a measure of a test's accuracy. It considers both the precision and the recall of the test to the F-measure can be interpreted as a weighted average of the precision and recall, where

F-measure reaches its best value at 1 and worst score at 0. The traditional F-measure is the harmonic mean of precision and recall:

$$F - Measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

The v3+v10+v1+v6+v5+v4+v2 nodes were tested using the K-Star classifier, by varying the number of global blends to pinpoint the optimum number of objects with the highest accuracy.

Figure 11 shows that the optimum number of global blends is 22 with an accuracy of 91.741%. The table shows the detailed accuracy by class for the SYM 8 wavelet. For the class loads, with 10%, 20%, 40%, 60%, 80% and 100% fault, 54 samples from each condition were collected.

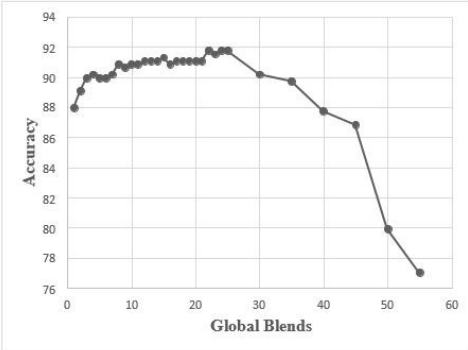

Figure 11. Accuracy versus global blends.

3. Results and Discussion

Vibration signals from a helical gearbox were recorded. 54 discrete wavelets were obtained and were used to carry out feature extraction. The signals were divided into 8 distinct groups (symlets), each symlet containing 54 different wavelet samples. These were tested in the Weka[31] software using the J48 classifier algorithm. The group with the highest accuracy was visualized using the decision tree. The nodes of the tree were separately evaluated to learn about their individual accuracies. Upon deriving the nodes with the maximum accuracy, the K-Star algorithm helped identify the optimum number of objects for the given nodes.

3.1 Feature Classification

The confusion matrix for the best fit tree has been presented in Table 2. The vibration signals were recorded for normal and abnormal conditions of helical gearbox. Totally 448 samples were collected; out of which 64 samples were from Healthy condition. For faulty load with 10%, 20%, 40%, 60%, 80% and 100% fault, 64 samples from each condition were collected. The statistical features were treated as features (attributes) and act as inputs to the algorithm. The corresponding status or condition (10% fault, 20% fault, 40% fault, 60% fault, 80% fault, 100% fault and healthy) of the classified data will be the required output of the algorithm. This input and corresponding output together forms the dataset. The dataset is used with decision tree J48 algorithm for generating the decision tree for the purpose of feature selection. Although the nodes closer to the root are more significant, all nodes in the tree are given equal importance for feature subset selection in order to maintain simplicity of the code.

The interpretation of the confusion matrix is as follows: The diagonal elements in the confusion matrix show the number of correctly classified instances.

- In the first row, the first element shows number of data points that belong to 'Good' class and classified by the classifier as 'Good'.
- In the first row, the fourth element shows the number of data points belonging to 'Good' class but misclassified as '30% fault'.
- In the first row, the seventh element shows the number of 'Good' data points misclassified as '100.0% fault'.
- In the first row, second, sixth and seventh elements represent misclassification of faulty conditions, denoted by '0'.
- However, there are misclassifications in other conditions. They are given in non-diagonal elements. Here, out of 448 data points, 37 data points were misclassified by the algorithm.

The summary of stratified cross validation obtained from the confusion matrix is given below:

Total Number of Instances	448	
Correctly Classified Instances	411	91.74%
Incorrectly Classified Instances	37	8.25%

The detailed class-wise accuracy of the J48 algorithm is presented in Table 3. Out of terms above in feature classification, TP rate and FP rate are important. The TP rate stands for true positive and its value should be close to 1 for better classification accuracy. The FP rate stands for false positive and its value should be close to 0 for better classification accuracy. In the study, the value of TP rate is

Table 2. Confusion matrix of best fit tree

Good	10PF	20PF	30PF	40PF	80PF	100PF	Classified as
59	0	1	3	1	0	0	Good
0	57	5	0	0	1	1	10PF
0	10	54	0	0	0	0	20PF
2	0	1	59	2	0	0	30PF
0	0	1	4	59	0	0	40PF
0	1	0	0	0	63	0	80PF
0	0	0	0	1	3	60	100PF

Table 3. Detailed accuracy table of best fit tree

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC-Area	Class
	0.922	0.05	0.967	0.922	0.944	0.986	GOOD
	0.891	0.029	0.838	0.891	0.864	0.984	10PF
	0.844	0.021	0.871	0.844	0.857	0.98	20PF
	0.922	0.021	0.881	0.922	0.901	0.995	30PF
	0.922	0.016	0.908	0.922	0.915	0.988	40PF
	0.984	0.003	0.984	0.984	0.984	0.999	80PF
	0.938	0.003	0.984	0.938	0.96	0.999	100PF
Weighted Avg.	0.917	0.014	0.919	0.917	0.918	0.99	

close to 1 and FP rate close to 0. The both values confirm that the built model is good one.

4. Conclusion

Gears are important machine elements in industrial machinery which are subjected to wear and tear. This paper applies the concept of data mining[32] and presents an algorithm based interpretation of vibration signals for fault diagnosis of helical gearbox. Discrete Wavelet Transform (DWT) was used to obtain the different wavelets. Sym8 wavelet was selected among these wavelets due its high accuracy as shown in Figure 8. J48 decision tree classifier was used to carry out the feature selection process. The decision tree was studied and the sequence of nodes was visualized. The different combinations of nodes were analyzed with the K-Star algorithm and V3+V10+V1+V6+V5+V4+V2 nodes had the highest accuracy. By varying the number of global blends, 22 was the optimum number obtained, an accuracy of 91.741. The accuracy is higher than the results obtained in previous research papers which had conducted fault diagnosis of helical gearboxes. Hence, the results were satisfactory.

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