Fault Diagnosis of Helical Gear Box using Vibration Signals through Random Tree and Wavelet Features

Abhi Srivastava¹*, Ameet Singh¹, V Sugumaran¹ and M Amarnath²

¹School of Mechanical and Building Sciences, VIT University, Chennai - 600127, Tamil Nadu, India; abhi.srivastava706@gmail.com, ameetsinghsassan123@gmail.com, v_sugu@yahoo.com
²Department of Mechanical Engineering, IITDM, Jabalpur - 482005, Madhya Pradesh, India; amaranth.cmy@gmail.com

Abstract

Objectives: Gearbox, being an important component in the mechanism of many industrial machines can have a few faults mostly by fatigue cracking under cyclic contact stressing. Most of the implements presently being utilized in the industries for the gearbox fault diagnosis are dependent upon the vibration signals which are accumulated from the gearbox. 

Methods: A machine based learning approach has been utilized for the detection of faults with the utilization of vibration signals that have been acquired from helical gearbox setup. The features were extracted from the collected vibration signals using wavelets. The significant features were selected using a Decision Tree algorithm. The selected features from this approach were then classified using random tree algorithm and higher accuracy was achieved. 

Findings: The random tree algorithm used for the classification of the wavelets which were extracted from the vibration signals of the gearbox resulted in a classification accuracy of 90.4%. This classification accuracy is unique in terms of the vibration signals that have been acquired utilizing the accelerometer from the helical gearbox setup. The higher classification is achieved after feature extraction, selection and classification.

Improvements/Applications: The classification accuracy achieved using the random tree algorithm was higher than the previously attained values for the gearbox. The higher accuracy would result in better fault diagnosis for the helical gearbox setup.

Keywords: Decision Tree, Fault Diagnosis, Helical Gearbox, Machine Learning, Random Tree Algorithm, Wavelet Features

1. Introduction

Gearbox enhances the performance of the engine by transmitting power using a set of gear ratios. Gearbox is primarily designed for the conversion of speed and torque thus providing a rotational energy source which further helps in the transmission of power from one machine to another. These set of gear ratios are used for the increased or decreased transmission depending upon the requirement of the machine. A conventional helical gearbox consists of case hardened and profile ground steel gears with inclined tooth to transmit the torque between parallel shafts with minimum noise. These helical gearboxes are ideal for very high power transmission systems i.e., greater than 50 kW. Gearbox finds its application in conveyors, crushers, cranes, larger ball mills, mixers, aerators, coal pulverising mills, plastic extruders. Thus being an important component in the sugar, cement, paper, plastic, rubber, steel industry, power plants, the faults inside the gearbox components must be reduced. The gearbox thus requires condition monitoring to maintain the overall system availability by reducing the amount of secondary damage which are caused by these gearbox failures. The defects in the gearbox include tooth breaking of gears which may be due to this misalignment or improper meshing of the gears, resulting in damaging the other gears and shaft, bending of the shaft as the broken piece would also be present inside increasing the amount of damage. Other defects in the gearbox include excessive heat generation, wear and tear in the gears. As the gearbox operates at various loads and speeds, the measurement of severity of the faults becomes difficult. Thus, different
types of signals are recorded for the detection of faults like vibration signals, sound signals and acoustic emission signals. For this study, vibration signals are recorded from a helical gearbox. When the system is running in normal condition, some amount of vibration is always present, however, during any faulty conditions the vibration frequency changes from the normal value i.e., it deviates from the normal vibration. There are three steps involved in diagnosing faults using machine based approach which are: Feature extraction followed by feature selection and at last feature classification. The features may be classified into statistical features, wavelet features or histogram features. For this study wavelet features were used.

The features are first extracted from the recorded vibration signals in the form of Symlet wavelets. The feature selection techniques include the concept of Decision Tree (DT), Genetic Algorithm (GA), Principal Component Analysis (PCA), etc. The method used for feature selection was using Decision Tree which can easily identify the best features from the data sets. There are 13 features which contribute to the accuracy percentage which will determine the amount of fault in the gearbox. The feature classification of the vibration data sets can be done using the classifiers: Support Vector Machine (SVM), Proximal Support Vector Machine (PSVM), Fuzzy, Decision Tree etc.

Over the last few years lots of research has been done to diagnose the gearbox system from faults. Previously, by performed fault diagnostics for rotating machinery using the Artificial Neural Network taking wavelets as a pre-processor; however, the accuracy was not that good. Moreover, the technique used requires greater computational burden and proneess to over fitting. Around the same time, by with the help of Wigner-Ville distribution and pattern recognition performed analysis for the detection of faults inside the gearbox using the time frequency analysis. This distribution method and pattern recognition showed greater impacts when diagnosing the gearbox for faults for the detection of breakage of gear tooth but some amount of noises are left inside the signal when using this technique. Later due to the advancement in technology, Z. K. Peng et al. provided us the result which shows that the wavelet transform started playing a major role in the condition monitoring and fault diagnostics. These wavelets are used for the diagnostics till date. The gearbox fault diagnostics improved even more with the involvement of empirical mode decomposition and Hilbert spectrum. The proposed method was used to verify the simulated signals and vibration signals which were collected from a gearbox dynamics simulator. Hilbert was also used with wavelet packet transform by. In found a way to predict and control the gearbox noise and vibration. He focussed completely on the control of noise due to the vibration analysis and the tatra truck power train system was used. In used support vector regression to find out the remaining useful life of the bearings. The resultant classification accuracy of 87.15% was achieved. Condition monitoring methods for the fault diagnostics of planetary gearboxes was used by. Vibration sensors and acoustic emission were used by for the fault diagnostics of gearbox tooth cut. Also, Shannon entropy and the applications of wavelet energy were used for the fault detection in a gearbox under varying speed conditions by. The wavelet coefficients energy and Shannon entropy are used as new parameters along with statistical parameters as an input for the classifier. The frequencies predicted for the observed faults in the annulus as well as the sun gears of the gearbox are presented using the frequency spectrum experimentally. L. Hong et al. also used a time domain approach for the diagnostics of gearbox faults using vibration signals. This time-domain fault diagnostics method combines the Correlated Kurtosis (CK) as well as the Fast Dynamic Time Warping techniques (FDTW) for the characterization of the local gear fault and also for the detection of position of the fault within the gearbox. A classification accuracy of 85.23% was achieved by Sugumaran et al. with the use of Decision Tree and best first tree for the fault diagnosis of a helical gearbox. A model for diagnosing faults was developed by. Vibration signals were used in the Naïve Bayes and Bayes net method used by to classify the faults present in a helical gearbox. The classifiers in Naïve Bayes and Bayes net require a big data set in for the probability estimation of each class. If the algorithm is used with a small data set, the precision of estimation for the information of each class will be very low. However, the classification accuracy achieved was 92.86% which is greater when compared to decision tree. In performed fault diagnosis on a spur bevel gearbox making use of Proximal Support Vector Machine (PSVM) and Artificial Neural Network (ANN). The ANN technique used requires greater computational burden and proneess to over fitting, whereas the drawback of SVM is that, these are not efficient for very high number of features. The SVM do not perform well on highly skewed data sets. In also developed a fault diagnosis model for spur bevel gearbox using discrete
wavelet features and Decision Tree classification\textsuperscript{21}. In this condition monitoring technique only the debauchee wavelet feature has been employed whereas in this paper all the seven families of wavelets have been employed for the fault diagnosis of helical gearbox. In\textsuperscript{22} used adaptive redundant lifting scheme for the gearbox fault diagnosis but due to its certain limitations, the accuracy achieved was not very high\textsuperscript{22}. Adaptive wavelet filters were utilized by\textsuperscript{23} for the gearbox fault detection\textsuperscript{23}. The fault diagnosis performed was effective as well as efficient. Another new method of adaptive stochastic resonance method was used for the fault diagnostics of planetary gearbox by\textsuperscript{24}. In\textsuperscript{25} showed the wavelet transform applications in the fault diagnostics of the gearbox\textsuperscript{25}. In\textsuperscript{26} used wavelet decomposition technique for the condition monitoring of the bearing health\textsuperscript{26}. The methods used previously for the fault diagnostics analyses the computational complexity which creates problems in fault detection. Although major fault diagnostics was successfully achieved but it required a rather complex circuits which is a difficult process. The classification accuracy achieved for the various features and classifier parameters was not that high considering the amount of complex systems.

In this paper another machine based approach is used along with the random tree algorithm for the feature classification. The vibration signals were recorded from a real helical gearbox and these signals were extracted using wavelet features converting them into Symlet wavelets which were classified using the random tree algorithm. The classifier model has been chosen to minimize the training time and give the highest classification accuracy. The conditions taken for the gearbox model are GOOD, 10%, 20%, 40%, 80% and 100% faulty conditions. Sym7 is the feature used for feature extraction as it provides better classification accuracy compared to the others. The results and discussions for the diagnosis of fault in helical gearbox with the use of vibration signals and wavelets are presented.

2. Experimental Studies

For the study of fault diagnosis in a helical gearbox the test setup was constructed. The experimental setup and procedure for the experiment are discussed below.

2.1 Experimental Setup and Procedure

The experimental arrangement used comprises of a 5 HP two stage helical gearbox. The gearbox is driven by a 3 phase induction motor of 5.5 HP. The 3 phase induction motor has an average speed of about 1440 RPM. The induction motor needs to be controlled for the setup to work constantly. Thus to control it, it coupled to an inverter drive. The speed at which the system is run is approximately 80 RPM. The experimental setup for the study is shown in Figure 1. The step up ratio for the gearbox is 1:15, thus at the speed of about 1200 RPM for the pinion shafts, the power transmission at the initial stage is approximately 2.6 HP which is very less as compared to its rated power of 5 HP. The power transmitted is so less due to the pinion, the pinion being connected to a DC motor generates a power of approximately 2 KW. This power generated by the DC motor gets dissipated in the resistor bank thereby decreasing the overall output at the initial stage of the gearbox. The load consumption inside the industrial surroundings varies from 50-100 %. Additionally, due the instabilities in turning force values torsional vibrations may arise, which could be minimized by using a DC motor and resistor bank. The overall specifications for the test rig are shown in Table 1.

![Figure 1. Experimental setup of two stage helical gearbox.](image-url)
sample frequency for the test was fixed at a frequency value of 8.2 kHz in accordance to the NY Quist sampling proposal. The aggregate number of sample signals are 448, which were distributed on 7 classes with each class consisting of 64 sample signals with the length of a sample signal be 8192 (2).

Table 1. Specifications of helical gearbox

|                | Initial stage | Secondary 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        | 1200 RPM (output) |

The local faults inside a gearbox are categorized in three classes. 1. Surface wear of the gears, 2. Cracked tooth of the helical gears and 3. Loss of a portion of the gear tooth due to its breaking at the working tip of the helical gear or at the root position. Many methods may be used to simulate the faults in gear such as Electric Discharge Machining (EDM). The simplest way to simulate faults in a gear is by partially removing the gear tooth. This technique simulates the faults of incomplete breakage of tooth, which is as often as possible saw in a few mechanical applications. The vibration signals were recorded with the help of accelerometers. The recorded vibration signals were then extracted using the MATLAB through different wavelet features. These extracted features were then classified using a Decision Tree classifier.

3. Methodology

The vibration signals were recorded using an accelerometer on a real gearbox model at good and faulty conditions. The vibration signals were then extracted to wavelet packet features using MATLAB provided by\textsuperscript{27}. These data sets were then analysed using a machine learning approach which involves feature extraction, feature selection followed by feature classification. A Decision Tree was generated using the random tree algorithm to classify faults. The contribution of various features in fault diagnostics was obtained. The steps followed can be observed in Figure 2.

3.1 Feature Extraction

The vibration signals are taken experimentally from the real gearbox under normal and abnormal conditions using an accelerometer. These vibration signals are then extracted by using wavelet features through MATLAB. The vibration signals recorded were time-domain signals. The time-frequency information from time-domain signals are extracted using Wavelet Packet Transforms (WPT)\textsuperscript{28}. The wavelet decomposition was performed on the vibration signals obtained using Discrete Wavelet Transform (DWT)\textsuperscript{29}. The trends and details were the outcome of decomposition. Trends are the low frequency signals whereas details are the high frequency signals. For every next level trends and details, the previously obtained trends after the decomposition were decomposed again. With the repetition of each next level trend, previous levels of trends are decomposed and many levels of details are obtained in this process. There were overall 13 levels of decompositions as the length of the signal is 2 (8192). The 13th feature which is also the last level of decomposition has the clearest frequency free from all kinds of noises as they are removed at each level of decomposition.

The feature vectors were defined at each stage as V1, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13, where V1, V2….V13 are the energy content given at each stage of the extracted features. The wavelets considered for the fault diagnosis include Haar wavelet, Discrete Meyer wavelet, Daubechies wavelet – db1, db2, db3, db4, db5, db6, db7, db8, db9, db10, biorthogonal wavelets (BIOR) –
bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8, reversed biorthogonal wavelets - rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8 coiflets – coif1, coif2, coif3, coif4, coif5. The vibration signals were finally converted to symlet wavelets in the feature extraction process which were analysed using the machine based algorithm. The Symlet features extracted from the vibration signals were: sym1, sym2, sym3, sym4, sym5, sym6, sym7 and sym8.

3.2 Wavelet Selection

The time–domain signals were processed from seven wavelet families using 54 different discrete wavelets for the selection of wavelet. The extracted features were classified through random tree algorithm using weka 3.6 and maximun classification accuracy for the wavelet was obtained (Figure 3 to Figure 9). Sym wavelet 7 gave the highest classification accuracy when it was classified through random tree as compared to all DWT’s mentioned above. The symletN, is also called as sym N, where N is the order. Sym wavelet characteristics can be defined as compactly supported wavelets with slightest geometry and highest act of vanishing moments for a given support width i.e. 2N-1. The length of filter is 2N. For orthogonality conditions, the solutions are 2N-1. Thus, the highest produced scaling filter of solution is selected as the outcome.

![Figure 3. Bior wavelets vs. classification accuracy %](image)

![Figure 4. Coif wavelets vs. classification accuracy %](image)

![Figure 5. Daubechie wavelets vs. classification accuracy %](image)

![Figure 6. Wavelet features vs. classification accuracy %](image)

![Figure 7. Rbio wavelet vs. classification accuracy %](image)
3.3 Feature Selection

The feature selection was done using the random Decision Tree algorithm and principal component analysis. A visualisation Decision Tree is obtained on the value of high accuracy. These features are then selected according to their place in the Decision Tree arranged in order of their contribution for the fault diagnosis inside the component. The Decision Tree for the data sets is depicted in Figure 10.

According to the Decision Tree, the top most feature V6 contributes maximum for the classification accuracy with about 48.44%, the next features V6 and V4 contributed 67.86% with the individual contribution being 19.42%, further V6, V4 and V1 resulted in 81.03% with V1 contributing to about 13.17%. The first four features V6, V4, V1 and V3 collectively gave the accuracy level to be 85.04%. The contribution of V6, V4, V1, V3, V8 and V2 combined was found to be 88.39%. The top 9 features V6, V4, V1, V3, V8, V2, V7, V5 and V10 combined gave a high accuracy output value of 89.96%. The contribution sequence according to the Decision Tree is V6+V4+V1+V3+V8+V2+V7+V5+V10+V1+V9+V12+V13 with all the features combined giving a classification accuracy of 90.4018%. The contributions of all features combined are displayed in the Figure 11.
3.4 Feature Classification

This comprises of the various types of classifiers which are used in the machine based algorithm for the detection of faults of the data sets. Random tree algorithm has been used for classification in the present study. The random tree algorithm classifier parameters include maximum depth and number of instances (K). The parameters are used to obtain the values of classification accuracy at different conditions so as to select the highest values from those conditions. These parameters were varied according to their limiting values to obtain the highest classification accuracy. Firstly, the parameter of maximum depth was varied without changing the number of instances (K) to find the maximum accuracy at certain depth value. The depth value was changed from 1-10 with a unit increment at each succeeding value. At depth = 1, the classification accuracy was 19.64%. With the increase in depth value, the accuracy was obtained to be 30.8% at depth = 2. At maximum depth = 3, the accuracy percentage is 46.43%. The highest accuracy value was obtained at a depth of 10. The classification accuracy obtained was 85.71%. The classification accuracy values with the change in maximum depth are depicted in Figure 12.

Now the number of instances (K) was varied keeping the maximum depth constant = 10 to obtain the highest possible accuracy level. The number of instances (K) was varied from the values of 1-15 with a unit increment at each step. At K = 1, the classification accuracy was 76.12%. With the increment in K value, the accuracy is found to be 82.82% at K = 2. The highest accuracy value was obtained at K = 10. The highest possible classification accuracy was found out to be 90.4%. The classification accuracy percentage with the variation in K value is depicted the Figure 13.

![Figure 11. Features vs. accuracy.](image)

![Figure 12. Maximum depth vs. accuracy.](image)

3.5 Random Tree Algorithm

During the construction of each tree, the algorithm takes a certain continuing feature randomly at every expansion of the node without any prior purity function check. The feature selected is categorized as continuing if it has not been chosen before in that particular decision from the starting roots of the tree to the current node where it is being evaluated. This tree continues to grow until and unless a few of the conditions have been fulfilled: 1. There are no more features to split in the current node i.e., the current node become empty, 2. The depth of the Decision Tree with all the features becomes too large and exceeds certain limits.

The parameters of the random tree algorithm like depth and k value are varied to get the maximum accuracy possible and then a Decision Tree is plotted. The maximum value of parameters can be achieved by keeping one parameter constant and varying the other to get the highest accuracy value. The value of parameters is noted and used to obtain the individual contribution by the features with the help of Decision Tree. The individual contribution by the features is noted with the top feature.
Fault Diagnosis of Helical Gear Box using Vibration Signals through Random Tree and Wavelet Features

giving maximum output. A higher accuracy percentage is attained.

A more suitable, way of viewing random tree models is by the splitting process which is determined by splitting probabilities, which in the binary case can be explained\(^3\). A group G is split recursively into two subgroups L and R, where, L (for left) and R (for right) and follows the equation \(|L| + |R| + \Delta = |C|\). Here \(\Delta\) is either 1 or 0. This value depends on whether the internal nodes contain information (retain elements of G) or not. The splitting probabilities completely characterize the process.

\[
\pi_{n,k} = \frac{k!}{n!} \Pr[L = k (|G| - n)]
\]  \hspace{1cm} (1)

And a termination rule, which is usually \(|G| \leq 1\). The three basic models we consider are:

- The uniform model in which all binary trees of size are taken to be equally likely. Thus it has \(\Delta = 1\), and will be seen to correspond to the splitting probabilities:

\[
\pi_{n,k} = \frac{b_k}{b_n} \quad \frac{n-1-k}{n} \hspace{1cm} (2)
\]

Where

\[
b_m = \frac{1}{m+1} \binom{2m}{m}
\]  \hspace{1cm} (3)

- Second is the binary search tree model, in which \(\Delta = 1\) and splitting probabilities given by:

\[
\pi_{n,k} = \frac{1}{n} \hspace{1cm} (4)
\]

- Lastly, the digital tree model, in which \(\Delta = 0\) and splitting probabilities given by:

\[
\pi_{n,k} = \frac{1}{2^n} \binom{n}{k} \hspace{1cm} (5)
\]

4. Results and discussion

A total of 448 samples were taken at both good and faulty conditions. Out of these 448 samples, a total of 405 samples were correctly classified using the random tree algorithm while the rest 43 were incorrectly classified. During this classification, the mean absolute error was calculated to 0.026 while another relative absolute error was 10.63%. The results are depicted below:

- Correctly Classified Instances: \(90.4018\%\) (405)
- Incorrectly Classified Instances: \(9.5982\%\) (43)
- Root relative squared error: \(44.5641\%\)
- Total Number of Instances: \(448\)
- Mean absolute error for the data: \(0.026\)
- The root mean squared error: \(0.156\)
- Relative absolute error for the data: \(10.6326\%\)

The results obtained from the random tree algorithm at the highest classification accuracy value with GOOD, 10%, 20%, 30%, 40%, 80% and 100% faults are shown in the confusion matrix in Table 2.

| Table 2. Confusion matrix based on random tree algorithm |
|-------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| GOOD | 10PF | 20PF | 30PF | 40PF | 80PF | 100PF |
| GOOD | 59 | 0 | 1 | 4 | 0 | 0 | 0 |
| 10PF | 0 | 56 | 4 | 2 | 1 | 1 | 0 |
| 20PF | 0 | 9 | 53 | 0 | 2 | 0 | 0 |
| 30PF | 2 | 2 | 55 | 3 | 0 | 0 | 0 |
| 40PF | 0 | 0 | 2 | 5 | 55 | 0 | 2 |
| 80PF | 0 | 1 | 0 | 0 | 63 | 0 | 0 |
| 100PF | 0 | 0 | 0 | 0 | 0 | 64 | 0 |

The confusion matrix shows that there are 64 signal values in each of the conditions at Good, 10PF, 20PF, 30PF, 40PF, 80PF and 100PF where, PF refers to Percentage Fault. The diagonal elements in the matrix depict the number of correctly classified instances for the data sets of the helical gearbox. The matrix rows correspond to the classification achieved by the random tree algorithm whereas the matrix columns correspond to the actual classes.

In the foremost row, 59 out of 64 data points were correctly classified as GOOD, while 1 being misclassified as 20PF and the remaining 4 samples being misclassified as 30PF.

In the second row, 56 data points were correctly classified as 10PF, while 4 of the remaining were misclassified as 20PF, 2 being misclassified as 30PF and 1 each misclassified as 40PF and 80PF.

In the third row, 53 data points were correctly classified as 20PF, 9 data points were wrongly classified as 10PF and the remaining 2 were found to be misclassified as 40PF.

In the fourth row, 55 of the total 64 data points were found to be correctly classified as 30PF, 3 being misclassified as 40PF and 2 each wrongly classified as good, 10PF and 20PF.
The fifth row has 55 data points correctly classified as 40PF, 5 were found misclassified as 30PF and 2 each being misclassified as 20PF and 100PF combining together to form a total of 64 data points.

In the sixth row, 63 of the data points were correctly classified as 80PF while the remaining 1 sample was found to be misclassified as 10PF. In the last row, all of the 64 data points were rightly classified as 100PF. Thus, this was the 100% faulty condition in the helical gearbox.

Now the detailed accuracy value by class must be considered for the various classes from GOOD condition to 100PF. A lot of other factors must be taken including the TP rate, FP rate, Precision of the data, F-measure and ROC Area and finally the weighted average of the factors was obtained. Here is the detailed accuracy by class table from the current problem depicted in the Table 3.

The TP rate describes True Positive rate for the diverse classes from GOOD condition to 100PF which shows the correctly classified instances. To obtain the highest classification accuracy the TP rate must be close to 1. The average TP rate for the experiment is 0.904 which represents a classification accuracy of 90.4%. The FP rate is the False Positive values depicting the incorrectly classified instances during the classification process. Thus, the FP rate should be close to 0 so that minimum number of misclassification is present. Precision displays the percentage of instances of correct classifications performed with respect to the total number of instances. Precision reached its maximum at a value of 0.97 for the 100PF. Recall or sensitivity; it is the number of instances of correct classifications performed with respect to the number of returned results. In this case, it is equal to the TP rate. In F-measure condition, both precision and recall are combined and is termed as the harmonic mean of precision and recall. The classification accuracy is measured by the area under the ROC curve, where an area of 1 represents perfect test, while an area of 0.5 represents a worthless test. In this case the ROC area is between the ranges of 0.915-0.997 which proves that it is nearly a perfect test having a high accuracy value.

Random tree machine based algorithm was used to find out the classification accuracy from the various symlet features which were previously extracted from the vibration signals collected from a helical gearbox at various good and faulty conditions. The highest accuracy was found at sym7 feature with the value being 85.7143%. The classification accuracy with the different symlet features are displayed in the Figure 14.

Table 3. Detailed accuracy by class

| Class      | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Weighted Avg. |
|------------|---------|---------|-----------|--------|-----------|----------|---------------|
| GOOD       | 0.922   | 0.005   | 0.967     | 0.922  | 0.944     | 0.958    | GOOD          |
| 10PF       | 0.875   | 0.031   | 0.824     | 0.875  | 0.848     | 0.937    | 10PF          |
| 20PF       | 0.828   | 0.023   | 0.855     | 0.828  | 0.841     | 0.956    | 20PF          |
| 30PF       | 0.859   | 0.029   | 0.833     | 0.859  | 0.846     | 0.915    | 30PF          |
| 40PF       | 0.859   | 0.016   | 0.902     | 0.859  | 0.88      | 0.922    | 40PF          |
| 80PF       | 0.984   | 0.003   | 0.984     | 0.984  | 0.984     | 0.991    | 80PF          |
| 100PF      | 1       | 0.005   | 0.97      | 1      | 0.985     | 0.997    | 100PF         |
| Weighted Avg. | 0.904 | 0.016  | 0.905     | 0.904  | 0.904     | 0.954    |               |

Figure 14. Classification accuracy vs. symlet features.

This symlet feature was then taken to the maximum possible accuracy level by varying the different classifier parameters for the random tree algorithm. The individual contribution by the various features from V1 to V13 was observed using the Decision Tree and the overall contribution by all these features was calculated by the addition of individual contributions from V1 to V13 was found to be 90.4%, where V6 being the highest contributor, fol-
lowed by V4, V1, V3, V8, V2, V7, V5, V10, V11, V9, V12 and V13.

Thus the highest accuracy value (90.4%) using random tree algorithm for the vibration samples was found at number of instances (k) =10 and maximum depth = 10. The highest contributing feature was V6 giving 48.44% while all the features combined gave a good accuracy output of 90.4%.

5. Conclusion

An algorithm predicted description of the acquired vibration signals for the different gearbox conditions was presented by this paper for the automated evaluation of the gearbox through these signals. Fault detection classification accuracies of 90.4018% during the tests displayed excellent performance of the proposed model. This model also revealed that the projected formulation has the capability of identifying faults correctly in the range of 85-90%. The results showed that the proposed decision tree-based model is effective in assessing the condition of process machinery and forecasting unscheduled equipment breakdowns with better accuracy and with reduced human effort.

6. References

1. Ahmed Q, Anifowose FA, Khan F. System availability enhancement using computational intelligence–based Decision Tree predictive model. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability. 2015 Jul; 229(6):612–26.
2. Joshuva A, Sugumaran V, Amarnath M. Selecting kernel function of Support Vector Machine for fault diagnosis of roller bearings using sound signals through histogram features. International Journal of Applied Engineering Research. 2015; 10(68):482–7.
3. Suykens JAK, Gestel TV, Vandewalle J, Moor DB. A Support Vector Machine formulation to PCA analysis and its Kernel version I. 2003; 14(2):447–50.
4. Rafiee J, Arvani F, Harifi A, Sadegh MH. Intelligent condition monitoring of a gearbox using Artificial Neural Network. Mechanical Systems and Signal Processing. 2007 May; 21(4):1746–54.
5. Paya BA, Esat II, Badi MNM. Artificial Neural Network based fault diagnostics of rotating machinery using wavelet transforms as a pre-processor. Mechanical Systems and Signal Processing. 1997 Sep; 11(5):751–65.
6. Staszewski WJ, Worden K, Tomlinson GR. Time–frequency analysis in gearbox fault detection using the Wigner–Ville distribution and pattern recognition. Mechanical Systems and Signal Processing. 1997 Sep; 11(5):673–92.
7. Hong L, Dhupia JS, Sheng S. An explanation of frequency features enabling detection of faults in equally spaced planetary gearbox. Mechanism and Machine Theory. 2014 Mar; 73:169–83.
8. Peng ZK, Chu FL. Application of the wavelet transform in machine condition monitoring and fault diagnostics. Mechanical Systems and Signal Processing. 2004 Mar; 18(2):199–221.
9. Liu B, Riemenschneider S, Xu Y. Gearbox fault diagnosis using empirical mode decomposition and Hilbert spectrum. Mechanical Systems and Signal Processing. 2006 Apr; 20(3):718–34.
10. Fan X, Zuo MJ. Gearbox fault detection using Hilbert and wavelet packet transform. Mechanical Systems and Signal Processing. 2006 May; 20(4):966–82.
11. Tuma J. Gear box noise and vibration prediction and control. International Journal of Acoustics and Vibration. 2009 May; 14(2):1–11.
12. Satishkumar R, Sugumaran V. Estimation of remaining useful life of bearings based on support vector regression. Indian Journal of Science and Technology. 2016 Mar; 9(10):1–7.
13. Lei Y, Lin J, Zuo MJ, He Z. Condition monitoring and fault diagnosis of planetary gearboxes. Measurement. 2014 Feb; 48:292–305.
14. Qu Y, He D, Yoon J, Hecke BV, Bechhoefer E, Zhu J. Gearbox tooth cut fault diagnostics using acoustic emission and vibration sensors - A comparative study. Sensors. 2014 Jan; 4(1):1372–93.
15. Bafroui HH, Ohadi A. Application of wavelet energy and Shannon entropy for feature extraction in gearbox fault detection under varying speed conditions. Neurocomputing. 2014 Jun; 133:437–45.
16. Hong L, Dhupia JS. A time domain approach to diagnose gearbox fault based on measured vibration signals. Journal of Sound and Vibration. 2014 Mar; 333(7):2164–80.
17. Sugumaran V, Amarnath M, Kumar H. Fault diagnosis of helical gearbox using Decision Tree and best first tree. International Journal of Research in Mechanical Engineering. 2013 Jul-Sep; 1(1):22–33.
18. Amarnath M, Kumar H, Sugumaran V, Jain D. Fault diagnosis of helical gear box using Decision Tree through vibration signals. International Journal of Performability Engineering. 2013; 9:221–34.
19. Amarnath M, Jain D, Sugumaran V, Kumar H. Fault diagnosis of helical gearbox using naive Bayes and Bayes net. International Journal of Decision Support System. 2015; 1:420–6.
20. Saravanan N, Siddabattuni VNSK, Ramachandran KI. Fault diagnosis of spur bevel gearbox using Artificial Neural
Network (ANN) and Proximal Support Vector Machine (PSVM). Applied Soft Computing. 2010; 10(1):344–60.

21. Saravanan N, Ramachandran KI. Fault diagnosis of spur bevel gearbox using discrete wavelet features and Decision Tree classification. Expert Systems with Applications. 2009; 36(5):9564–73.

22. Hongkai J, Zhengjia H, Chendong D, Peng C. Gearbox fault diagnosis using adaptive redundant lifting scheme. Mechanical Systems and Signal Processing. 2006; 20(8):1992–2006.

23. Lin J, Zuo MJ. Gearbox fault diagnosis using adaptive wavelet filter. Mechanical Systems and Signal Processing. 2003; 22(1):172–201.

24. Lei Y, Han D, Lin J, He J. Planetary gearbox fault diagnosis using an adaptive stochastic resonance method. Mechanical Systems and Signal Processing. 2013; 38(1):113–24.

25. Amarnath M, Swarnamani S, Sujatha C. Application of wavelet transform to gearbox fault diagnosis. Journal of Sound and Vibration. 1996 May; 192(5):927–39.

26. Priya VS, Mahalakshmi P, Naidu VPS. Bearing health condition monitoring: Wavelet decomposition. Indian Journal of Science and Technology. 2015 Oct; 8(26):1–6.

27. Li P, Jiang Y, Xiang J. Experimental investigation for fault diagnosis based on a hybrid approach using wavelet packet and support vector classification. The Scientific World Journal. 2014; 2014:10.

28. Yen, GG, Lin KC. Wavelet packet feature extraction from vibration monitoring. Industrial Electronic; 2000. p. 650–67.

29. Muralidharan V, Sugumaran V. Feature extraction using wavelets and classification through Decision Tree algorithm for fault diagnosis of mono-block centrifugal pump. Measurement. 2012; 47(3):353–9.

30. Flajolet P. Random tree models in the analysis of algorithms. Elsevier. 1988. p. 1–17.

31. Saravanan N, Ramachandran KI. Incipient gearbox fault diagnosis using Discrete Wavelet Transform (DWT) for feature extraction and classification using Artificial Neural Network (ANN). Expert Systems with Applications. 2010; 37(6):4168–81.