PAPER • OPEN ACCESS

Research on intelligent fault diagnosis of gears using EMD, spectral features and data mining techniques

To cite this article: M Sagar *et al* 2017 *IOP Conf. Ser.: Mater. Sci. Eng.* **263** 062047

View the article online for updates and enhancements.

Research on intelligent fault diagnosis of gears using EMD, spectral features and data mining techniques

M Sagar[1], G Vivekkumar[1], Mallikarjuna Reddy[1], S Devendiran[1] and M Amarnath[2]

[1]School of Mechanical Engineering, VIT University, Vellore - 632014, Tamil Nadu, India.

[2]Department of Mechanical Engineering, IIIT DM, Jabalpur, India.

Email: dmreddy@vit.ac.in

Abstract: In this present work aims to formulate an automated prediction model using vibration signals of various gear operating conditions by using EMD (empirical mode decomposition) and spectral features and different classification algorithms. In this present work empirical mode decomposition (EMD) is a signal processing technique used to extract more useful fault information from the vibration signals. The proposed method described in following parts gear test rig, data acquisition system, signal processing, feature extraction and classification algorithms and finally identification. Meanwhile, in order to remove the redundant and irrelevant spectral features and classification algorithms, data mining is implemented and it showed promising prediction results.

1. Introduction

Gear is one of the vital components used in rotating machinery for power transmission. The condition under which the gear operates adversely affects the performance of rotating machine. Fault in a gear is an unavoidable part and may result in abnormal behavior and often failure in the system. It is therefore necessary to detect the faults in gear and diagnose at early stages. Vibration analysis is one of the fault diagnosis methods, which is widely used because of simplicity in measurement. All the critical information in terms of faults can be obtained using vibration signal processing techniques. In diagnostics, signal processing technique is widely used to characterize the state of the system. Since the last decade several types of signal processing techniques have been developed. The results obtained from different types of signal processing techniques are often different from each other. Therefore, suitable techniques are selected for a specific system or component, depending upon the environmental conditions. Empirical mode decomposition (EMD) [1,2] is a signal processing method in which complicated data signals which are most often non-stationary or non-linear can be decomposed into intrinsic mode function (IMF) in finite set. These intrinsic mode functions are used to find the solution for Hilbert-Huang Transform [3]. Cheng et al. [4] proposed the concept of local Hilbert energy spectrum. Two gear fault diagnosis techniques were applied which included frequency family separation technique and local Hilbert energy spectrum technique to diagnose the gear with fault. Support vector machines (SVM) [5-7] are used in combination with IMF auto regressive models to identify the working condition of gear. Feature extraction of vibration signals of gear was done with the help of EMD. Faulty vibration signals of gear were extracted using the AR model. SVM was used to obtain the fault recognition pattern. Michael Feldman [8] explained how under the influence of harmonic functions the corresponding operational behavior of EMD changes. EMD technique is widely used in combination with other signal processing techniques such wavelet transform [9], Fourier transform and other such techniques for better

outcome. Lin and Hongbing [10] studied a new method for feature extraction of signals in which standard EMD method and the inverse EMD filters are combined to obtain a better decomposition technique of multicomponent signals. They proposed that inverse EMD filter has better performance for signals having lower frequency. Median filter is another processing method which can be combined with EMD to analyze friction signals [11]. Median filter is process is used to reduce random noise in the signals. Most often, unwanted noise is produced by the measuring system which can be removed using median filter. Amaranth and Praveen Krishna [12, 13, 17] investigated the surface wear failure in spur as well as helical gears using EMD technique. Ensemble empirical mode decomposition (EEMD) technique is used to extract feature related to faults for the vibration signals. In case of helical gear, EMD is applied to vibration and acoustic signals and based on the kurtosis value, for both the input signals and empirical mode decomposition obtained the upper hand of EMD is exhibited.Kedadouche et al [14] applied combination of EMD and Lempel-Ziv complexity method the detect damage in an early stage of gear. Hassan and Bhuiyan [15] demonstrated the effectiveness of sleep scoring algorithm combine with TQWT features. Mcfadden and Smith [16] explained how the defect influencing the dynamic characteristic of the rolling bear with radial load.

2. Process methodology:

In this study, EMD as a signal processing tool is used to find the intrinsic mode functions for the gear data obtained through experiments. The fault information acquired through EMD are then extracted and categorized into different spectral features [14]. Spectral features provide input to the data mining procedure which classifies the data through classification algorithm. This classified data is extensively compared to predict the health condition of gear. Figure1 depicts the process methodology presented in this paper and steps involved to diagnose the condition of the gear.
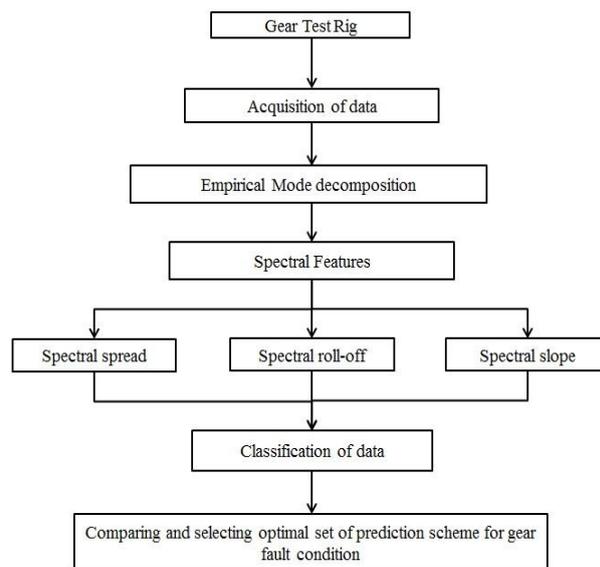

Figure 1. Process methodology

3. Experimental setup:

To study the wear of gear under accelerated test condition, the experiment setup was accordingly arranged. A gear test rig was used in this experiment. Two parallel shafts and four gears along with pinion and gear pairs were used in the arrangement. Gear box was parallel arranged in the system. A variable frequency drive (VFD) was used for controlling the speeds, three face 10HP induction motor and break drum dynamometer were connected to the gear box to control the loads, Tri axial accelerometer used to measure the vibration signals. For collecting the vibration data 24bit signal processor dewesoft analyzer and computer with data acquisition software were used. Rotating speed of the gear set was maintained constantly. Steady load was applied by brake drum dynamometer and the speed monitor by tachometer. And the fault size is maintained for all three components.
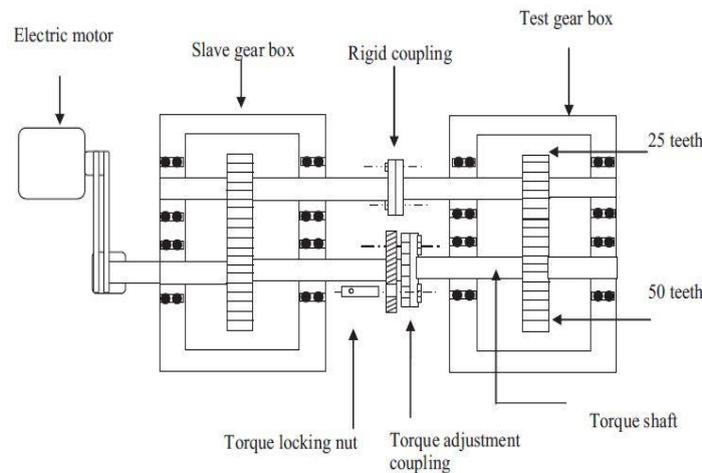
Figure 2. Layout of the experimental setup

For this experimental setup, the arrangement, the designing complexity of the driving system was significantly reduced. This approach of testing and investigating the gear system was all the more reliable. The gearbox used in the experimental setup was operated at 1700 rpm under accelerated test conditions. Vibration signals were captured by a tri-axial type accelerometer. A 24 bit data acquisition system which almost collects 5000 data points per second was used to capture the signals.

4. Theoretical background of EMD

Empirical mode decomposition method was derived and acknowledged by Huang as the fundamental part of Hilbert-Huang Transform (HHT) and he applied this time-space analysis method for the processing non-stationary as well as non-linear vibration signals. Without actually departing from time domainthe signal processing method is used to convert multi-component vibration signals into number of mono-component signals called as intrinsic mode functions (IMF) as they are called, using the EMD algorithm. An IMF is a function in the family of frequency that must satisfy the following two conditions: (1) in the entire set of data, the number of extreme and the number of zero-crossings must either equal or differ at most by one, and (2) at any point, the local average is zero, meaning the mean value of the upper envelope of data set (local maxima) and lower envelope of data set (local minima) is zero. This technique is all the more useful in analyzing the natural non-stationary signals. Table below depicts the process steps involved in EMD method considering a signal x (t) and the figure depicts the pictorial representation of this particular signal processing technique.

Table 1. Algorithm used for EMD

1) Initialize: $r_0=x(t)$, and $i=1$
2) Extract the ith IMF c_i.
a. Initialize: $h_{i(k-1)}=r_{i-1}, k=1$
b. Extract the local maxima and minima of $h_{i(k-1)}$.
c. Interpolate the local maxima and minima by cubic spline lines from upper and lower envelops of $h_{i(k-1)}$.
d. Calculate the mean $m_{i(k-1)}$ of the upper and lower envelops of $h_{i(k-1)}$.
e. Let $h_{ik}= h_{i(k-1)}- m_{i(k-1)}$
f. If h_{ik} is an IMF then set $c_i= h_{ik}$, else go to step (b) with $k=k+1$
3) Define the remainder $r_{i+1}=r_i-c_i$.
4) If r_{i+1} still has least 2 extrema then go to step(2) within=i+1 else the decomposition process is finished and r_{i+1} is the residue of the signal.

In the concluding part of the procedure a residue r_I is obtained and set of I IMFs c_i (i = 1, 2, . . ., I). Taking the summation of all IMFs and the final residue r_I we get, x (t) $= \Sigma_{i=1}^{I}c_i + r_I$. Hence, it is possible to decompose a signal into I IMFs and a residue r_I, which is the mean trend of x (t). The

IMFs, c_1, c_2, ..., c_i include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of the signal x (t), while r_I represents the central tendency of the signal x(t).
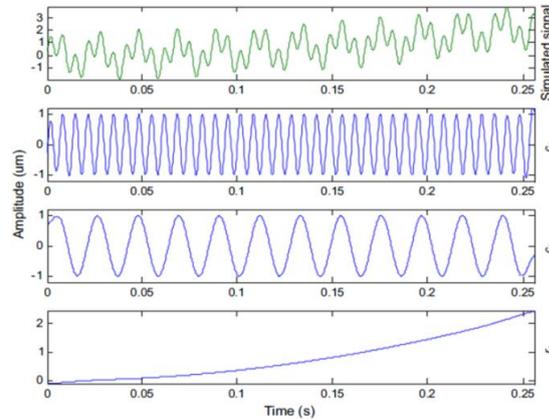

Figure3. EMD method employed for signal processing

5. Spectral Features:

Spectral features are thefeaturesbased on frequency domain used in audio and speech signal classification which are obtained by converting the time based signal into the frequency domain using the Fourier Transform, like: fundamental frequency, spectral slope, spectral decrease, spectraldensity, spectral roll-off, etc. These features can beused to identifythenotes, pitch, rhythm, and melody of a given input signal. In this paper application of spectralspread, spectralflatness, spectralslope, spectral decrease, and spectral roll-off are applied. A brief discussion is given in thebelow. Y(q) is thediscreteFourier transform (DFT) of y(m) where q = 0, 1, 2, . . ., M − 1. The magnitudespectrum of y(m) is theabsolutevalue of its DFT |Y(q)|.

5.1 Spectral spread

Spectralspread can also becalled as instantaneous bandwidth. Theconcentration of magnitudespectrum aroundthespectral centroid can be shown by using spectralspread. It can be also said as standard deviation of magnitudespectrum around thespectral centroid. It is expressed by

$$SS = \frac{\sum_{q=0}^{M-1}(q-SC)^2 \left|Y(q)\right|}{\sum_{q=0}^{M-1}\left|Y(q)\right|} \tag{1}$$

5.2 Spectralslope

Spectralslope evaluates thespectralshapeslope by using an approximation of themagnitudespectrumtechnique, linearregression is applied to find the approximation of themagnitudespectrum. Modeling a linear function from themagnitudespectrum of the faulty gear signal, spectral slope is calculated by using themathematical expression as follows.

$$SSl = \frac{M\sum_{q=0}^{M-1}F_m\left|Y(q)\right| - \sum_{q=0}^{M-1}\left|Y(q)\right|}{M\sum_{q=0}^{M-1}F_m^2 - (\sum_{q=0}^{M-1}\left|Y(q)\right|)} \tag{2}$$

5.3 Spectral roll-off

Spectral roll-off is nth percentile of spectral distribution of the signal. n ranges from 80% to 90 % it is thefrequencybelow which the nth percentile of themagnitude distribution is concentrated. Spectral roll-off computesthespectral energy concentration of thegiven input signal.

It is expressed as

$$SR = \sum_{q=0}^{m_c} |Y(q)| = \frac{C}{100} \sum_{q=0}^{M-1} |Y(q)| \quad (3)$$

6. Classification algorithms:

6.1 Classification through IBK

Setswhetherthemeansquarederror is utilizedinstead of meanabsoluteerrorwhile doing cross-approval. Setsthe most extreme number of casespermitted in thepreparation pool. IBKclassifier. Simpleinstancesoccurrencebasedlearner that usesthe class of theclosest k preparingcases for the class of thetestcases.

6.2 Classification through K-star

K-Star classifier is pa variant of p Lazy algorithms. K-Star uses an entropymeasure to transform a sample p to another, by randomly choosing k between possible g transformations. Given a set of samples s and a set of possible u transformations T, it will map s: S→S, that is, k is a sample (a) to anothersample (b). Then p T∗ consists of members that has unique h mapping on S, givenby

$$(a) = (sn-1(\ldots s1(a)\ldots)) \qquad\qquad\qquad (4)$$

where s=s1,…sn , the probability function on $T*$ is given by p. $P*$ is defined as the probability of all possible paths between *f*sample (*a*) and sample (*b*) and is given by

$$P* \times (ba) = \Sigma P(s)s \in pi:s(a)= \ b \qquad\qquad\qquad (5)$$

And hencethe$K*$ function is given as
$$K* \times (ba)= -log2P\times(ba) \qquad\qquad\qquad (6)$$

6.3 Classification through J48

J48 classifier is a straightforward C4.5 decision tree for classification. It makes a binary tree. TheDecision tree approach is most helpful in classification issue. With this procedure, a tree isdeveloped to show the classification process. Oncethe tree is assembled, it is connected to each tuple in thedatabase and brings about classification for that tuple. J48 permits classification. Through eitherdecision trees or rulescrated from them.

7. Results and discussions

To demonstratethe effectiveness of theproposed diagnosis method for thegear faults, the vibration data acquired from thegearsetupareused. Vibration signals have been decomposed into different frequencies i.e. IMF1, IMF2, IMF3, IMF4, IMF5 using EMD method. Time domain and correspondingfrequencyspectrum of different fault conditions aregiven in Figure4.
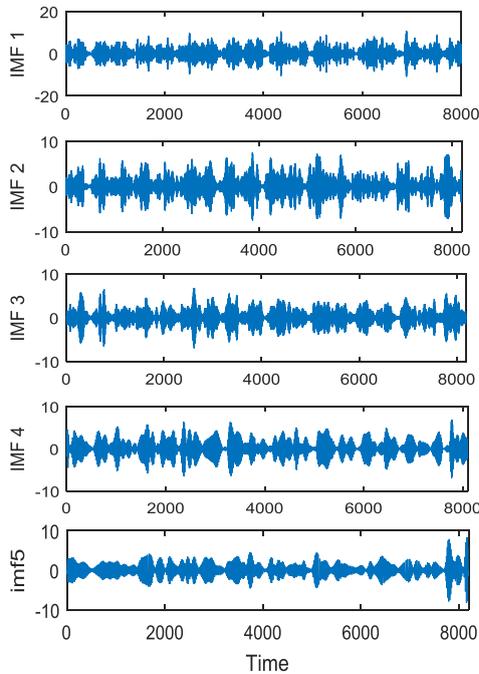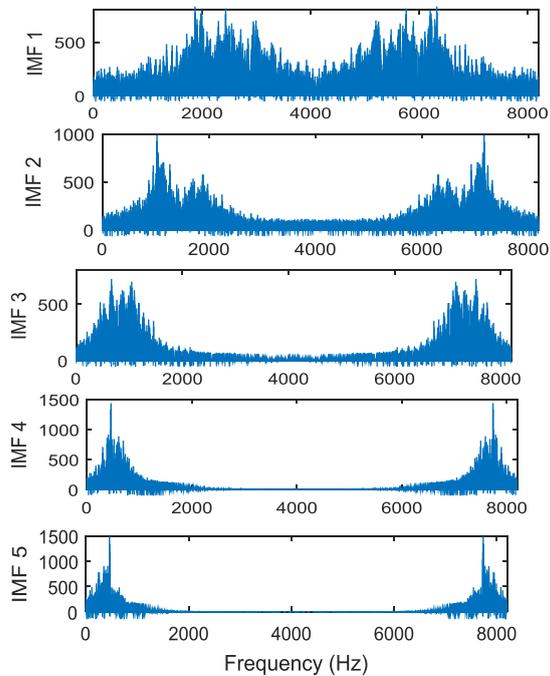

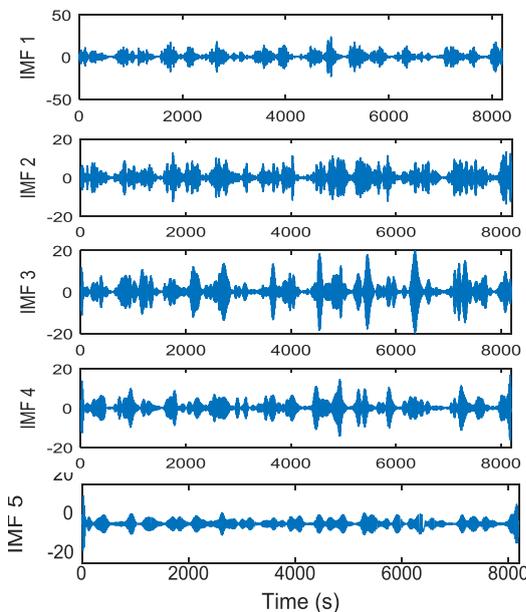**Figure 4 (a).**Time wave form of Gear 0Hr   **Figure 4 (b)**Frequency spectrum of Gear 0Hr
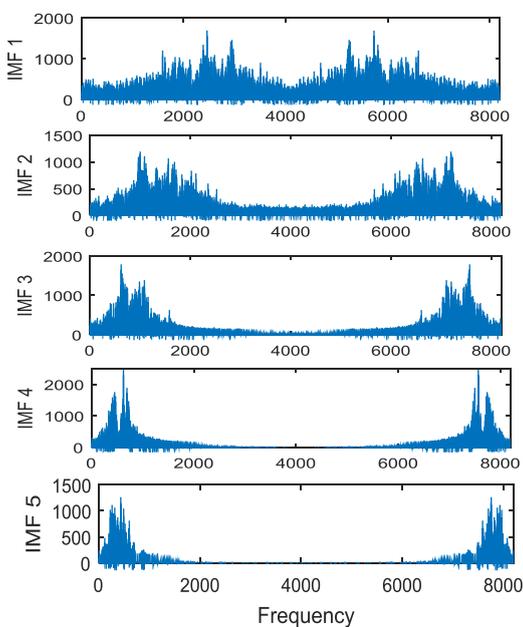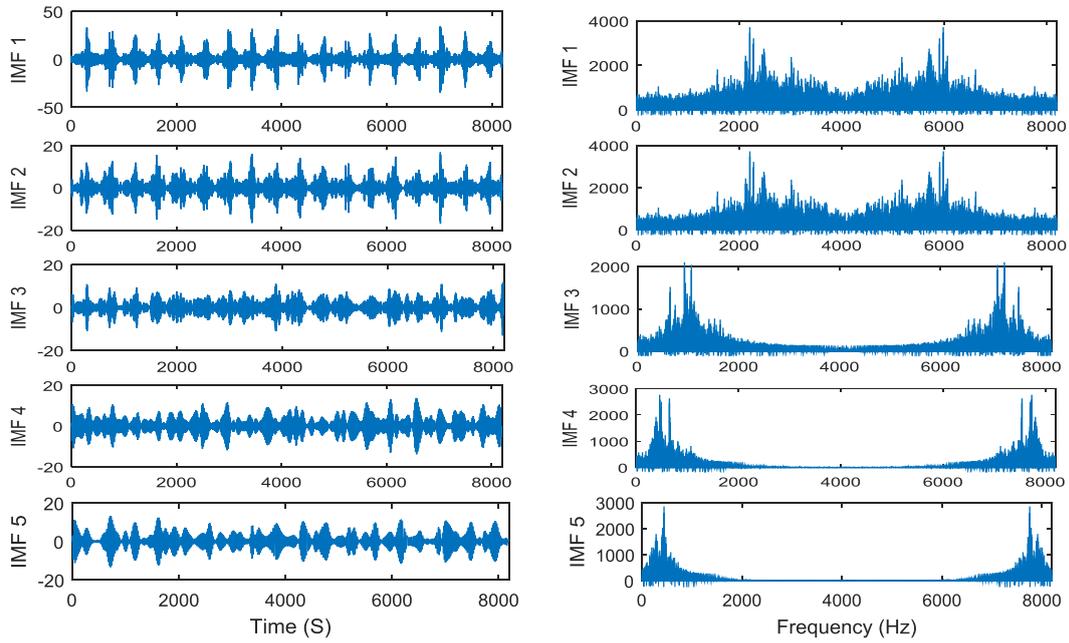

Figure 4 (c). Time wave form of Gear 36Hr**Figure 4 (d).**Frequency spectrum of Gear 36Hr

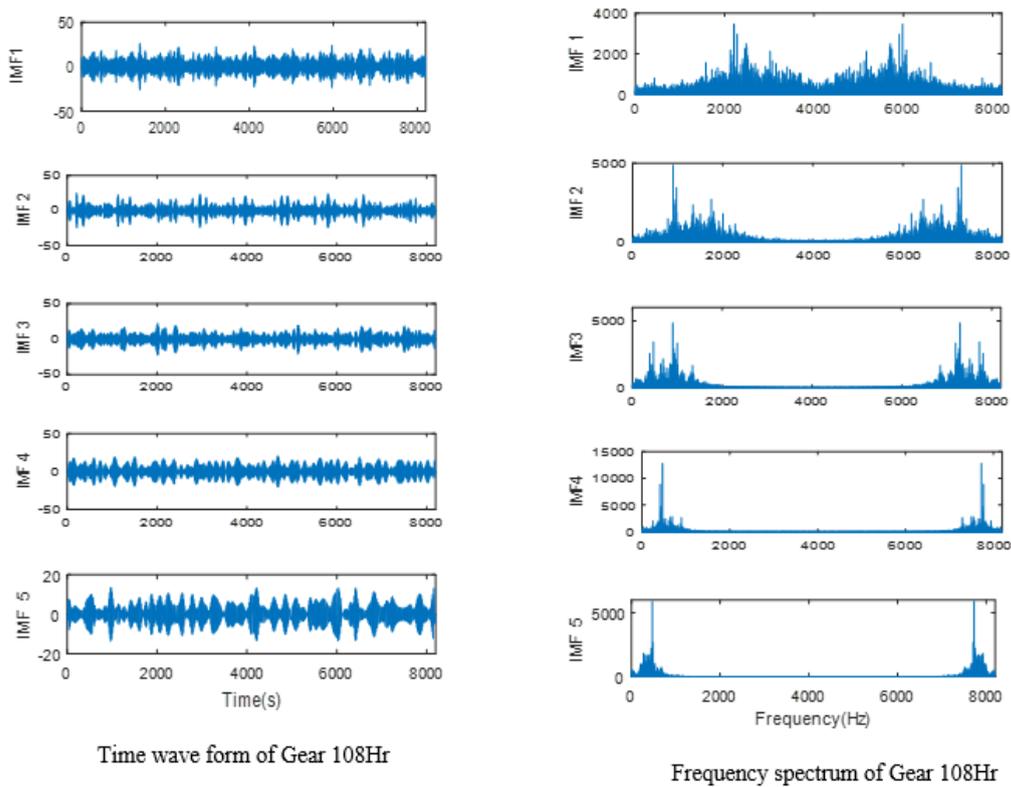**Figure 4 (e).**Time wave form of Gear 72Hr**Figure 4 (f).** Frequency spectrum of Gear 72Hr

Time wave form of Gear 108Hr

Frequency spectrum of Gear 108Hr

Figure 4 (g). Time wave form of Gear 108Hr**Figure 4 (h).** Frequency spectrum of Gear 108Hr

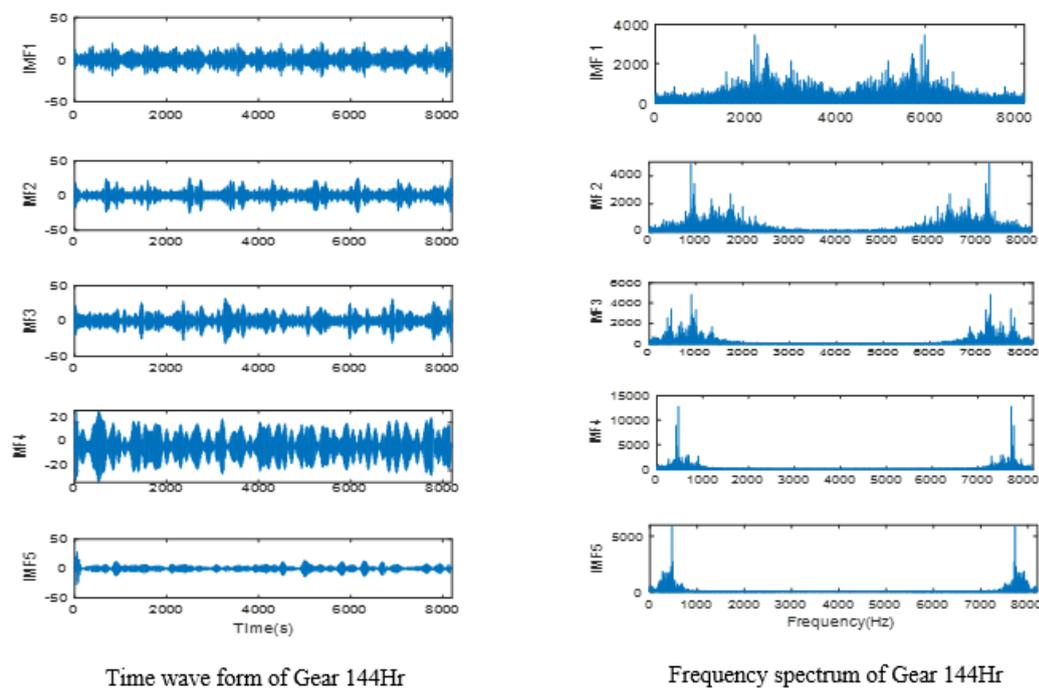Time wave form of Gear 144Hr   Frequency spectrum of Gear 144Hr

Figure 4 (i). Time wave form of Gear 144Hr**Figure 4 (j).** Frequency spectrum of Gear 144Hr

Figure4. Time domian and frequency domain of various time data set

The figures above represent the different spectrum of gear condition. In the corresponding frequency range of every IMFs say mode 1(frequency range of IMF1) contains the most signal frequencies, mode 2 the following higher signal frequencies. With the assistance of this information, the informative features in this automated fault diagnosis analysis approach, which are gathered from the gear fault frequencies, will give more prediction accuracy.

The selection of IMFS is based on following criteria. From the frequency spectrum for 0 hour data set of IMF 1 is centered from2000Hz to 4000Hz, in second IMF frequency spectrum is centered from 1000Hz to 4000Hz. In IMF3 it is centered form 500Hz to 2000Hz. In IMF4 frequency spectrum is centered from 200Hz to 1000Hz. In second condition, that is for 36 hours data set, of gear the IMF2 and IMF3 is cantered form1500Hz to 2500Hz.which can be associated with the characteristic bearing frequency of the component. Similarly in Fig6 (f) and Fig6 (h) the IMF2 and IMF3 is cantered from same range. IMFs in both frequency and time domain are clearer even if it is hard to find fault characteristics which can distinguish the all conditions. All the spectral features based features are normalized before given as input to the feature selection and classification algorithms.

In this present work feature selection process is done by working out with different classifiers. The feature selection processes were done in MATLAB. The input features are two types: Time and frequency domain features that are extracted from time and frequency IMFs of EMD and selected features from the same are separately fed input into WEKA classifiers such BayesNet, DMNBtext, Logistic, RBFnetwork, K-star, IBK, AttributeSelectedClassifier, Dagging, Hyperpipes, VFI, DTNB, JRIP, J48, LADTREE to find out the different states of gear. WEKA is open source software used for the data mining technique or in other words used to create classification algorithms.

The simulation results are shown in Table 2. and Table 3. Table 2 summarizes the result based on accuracy, time taken and kappa statistics for each simulation. Table.3 shows results based on errors. Figure 5 and figure 6 represent the graphical representation of simulation results. It can be clearly noticed that highest accuracy obtained is 99.5067% which belongs to the K-Star classification and lowest is 32.9561 % it belongs to Dagging classifier. It is noticed that IBK classification requires shortest time 0.26 seconds compare to the other classifications.

Table 2. Results of the classification algorithms with respect to accuracy category

Classifier	Classification	Correctly classified instances in %	Incorrectly classified instances in %	Kappa statistics	Run time
Bayes	BayesNet	56.3542	43.6458	0.45	0.33
	DMNB Text	76.6733	23.3267	0.55	0.54
Functions	logistics	98.2387	1.7613	0.95	0.32
	RBFNetworks	92.4576	7.5424	0.9	0.34
Lazy	IBK	98.1572	1.8428	0.95	0.26
	Kstar	99.5067	0.4933	0.98	0.28
Meta	AttributeSelectedClassifier	80.3728	19.6272	0.75	0.27
	Dagging	32.9561	67.0439	0.15	0.53
Misc	HyperPipes	82.6123	17.3877	0.85	0.28
	VFI	88.4231	11.5769	0.85	0.27
Rules	DTNB	56.1521	43.8479	0.45	0.35
	JRip	80.6612	19.3388	0.75	0.29
Trees	J48	84.9811	15.0189	0.8	0.28
	LADTree	56.6511	43.3489	0.45	0.27

Table 3. Results of the classification algorithms wih respect to error category

Classifier	Classifications	Mean absolute Error	Root Mean squared error	Relative Absolute error in %	Root relative squared error in (%)
Bayes	BayesNet	0.238	0.3301	74.3653	82.5301
	DMNBText	0.3049	0.3952	95.2677	98.8037
Functions	Logistics	0.1251	0.1465	14.656	13.325
	RBFNetwork	0.1732	0.1945	15.4207	23.6261
Lazy	IBK	0.1336	0.1767	16.667	16.667
	Kstar	0.1056	0.1241	12.345	10.567
Meta	AttributeSelectedClassifier	0.1044	0.2285	32.619	57.1131
	Dagging	0.3121	0.3929	97.5238	98.2202
Misc	HyperPipes	0.2846	0.3579	88.9285	89.4747
	VFI	0.2531	0.3224	79.5928	80.5928
Rules	DTNB	0.2557	0.3393	79.8992	84.8335
	JRip	0.12	0.2449	37.5	61.2372
Trees	J48	0.0907	0.2129	28.3333	53.2291
	LADtree	0.1909	0.3546	59.652	88.6501

Kappa statistics is utilized to evaluate the accuracy. It is normal to recognize the reliability of the data collected and their validity. Kappa > 0.75 as excellent, 0.40-0.75 as fair to good, and < 0.40 as poor. In this work .In this work kappa score for selected algorithms is around 0.11 to 0.99. K-star classification gives good status kappa value 0.98 and lead the list of the results.

In this present work normally utilized indicators, for example, mean absolute error and relative

absolute errors that belongs to regression absolute measure were implied and relative absolute error and root mean square error is derived from regression absolute measure and regression mean measure component . Lower error indicates that it has more powerful classification capability. It is observed that the lowest error is found in J48 network classifier in the entire of all sets of classification.
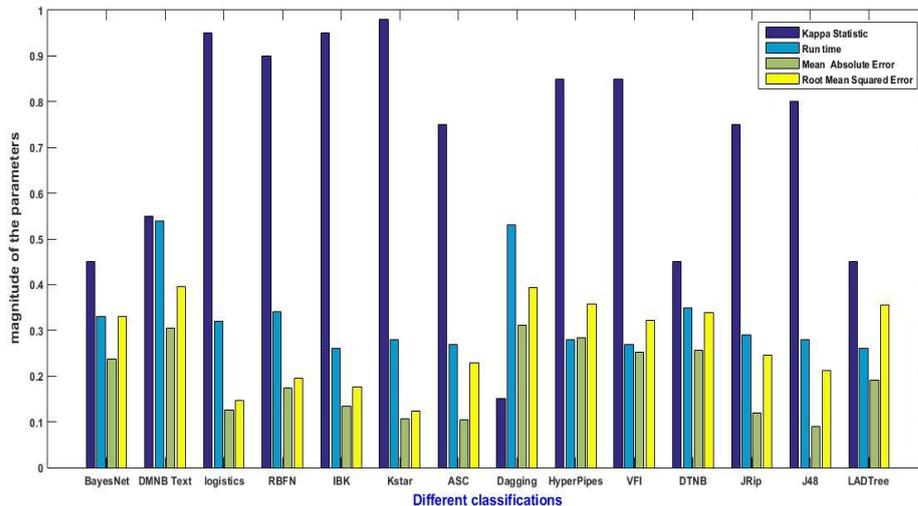

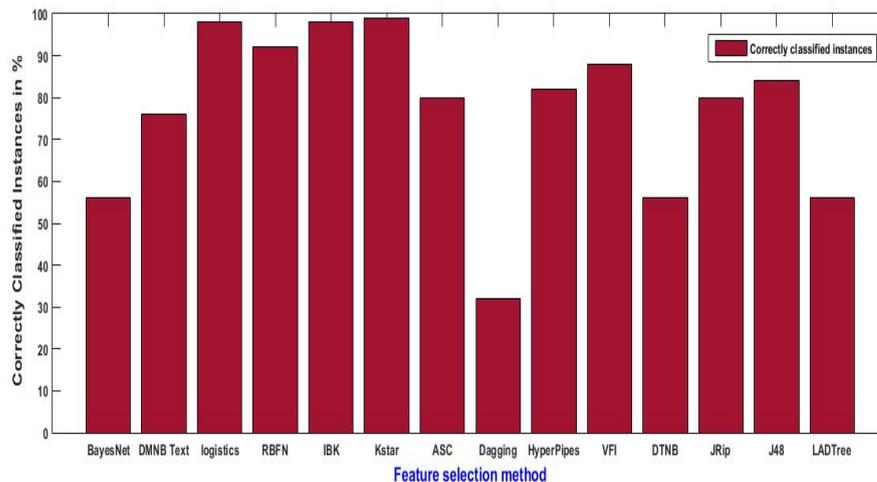**Figure5**. Comparison between different evaluation parameters of different classifications

Figure6. Comparison of different classifications under accuracy category

8. Conclusion

In this proposed work, therealtime experimental vibration data setsarecollected and used to valuatetheperformance in fault diagnosis of gears. EMD is used to extractcharacteristics from the non-stationary signal. Spectralfeaturesderived from IMFs of EMD on both time and frequency domain vibration signals of various faultless and faulty conditions of gear are used in this methodology. Meanwhile, in order to removetheredundant and irrelevantspectralfeatures and classification algorithms, data mining is implemented and it showed promising predictionresults.The final comparison resultsindicatethe effect of featureextractionbased on EMD and different classification algorithms. Altogether, EMD IMFs extracted spectralfeaturesoptimized by different classification process, and in contrast, K-star network classification givesbetterresults with respect to accuracy category with accuracy of 99.5067% compared to other classifications in thesame condition in gear fault diagnosis while J48 givesbetterresults with respect to errorcategory with absolutemeanerror of 0.0907 which theleast among all theother classifications.

References:

[1]   Yaguo Lei, JingLin , ZhengjiaHe , MingJ.Zuo 2013 A review on empirical mode decomposition in fault diagnosis of rotating machinery, *Mechanical Systems and Signal Processing* **35**:108–126.

[2]   Roberto Ricci, Paolo Pennacchi 2011 Diagnostics of gear faults based on EMD and automatic selection of intrinsic mode functions, *Mechanical Systems and Signal Processing* **25**:821–838.

[3]   T.Y. Wua, J.C.Chen , C.C.Wang 2012 Characterization of gear faults in variable rotating speed using Hilbert-Huang Transform and instantaneous dimensionless frequency normalization *Mechanical Systems and Signal Processing* **30**:103–122.

[4]   Junsheng Cheng , Dejie Yu , Jiashi Tang , Yu Yang 2008 Application of frequency family separation method based upon EMD and local Hilbert energy spectrum method to gear fault diagnosis, *Mechanism and Machine Theory* **43**:712–723.

[5]   Junsheng Cheng, Dejie Yu, and Yu Yang 2008 A Fault Diagnosis Approach for Gears Based on IMF ARModel and SVM", *EURASIP Journal on Advances in Signal Processing* , doi:10.1155/2008/647135 .

[6]   Zhongjie Shen, Xuefeng Chen, Xiaoli Zhang, Zhengjia He 2012 A novel intelligent gear fault diagnosis model based on EMD and multi-class TSVM, *Measurement* **45**:30–40.

[7]   N. D. Dushyanth, M. N. Suma Mrityanjaya V. Latte 2016 Detection and localization of damage using empirical mode decomposition and multilevel support vector machine,*Appl.Phys.A* 122:250.

[8]   Michael Feldman 2009 Analytical basics of the EMD: Two harmonics decomposition, *Mechanical Systems and Signal Processing* **23**:2059–2071.

[9]   Helong Li, Xiaoyan Deng, Hongliang Dai 2007 Structural damage detection using the combination method of EMD and wavelet analysis, *Mechanical Systems and Signal Processing* **21**:298–306.

[10]   Li Lin, Ji Hongbing 2009 Signal feature extraction based on an improved EMD method", *Measurement* **42**:796–803.

[11]   Kejian Guo, Xingang Zhang, Hongguang Li, Guang Meng 2008 Application of EMD method to friction signal processing, *Mechanical Systems and Signal Processing* **22**:248–259.

[12]   M. Amarnath, I.R. Praveen Krishna 2013 Detecttion and diagnosis of surface wear failure in a spurgeared system using EEMD based vibration signal analysis, *Tribology International* **61:**224-234.

[13]   M. Amaranth, I.R. Praveen 2014 Local fault detection in helical gears via vibration and acoustic signals using EMD based statistical parameter analysis, *Measurement* **58:**154-164.

[14]   M.Kedadouche, T.Kidar, M.Thomas, A.Tahan, M. El Badaoui and R. Guilbault, 2013 Combining EMD and Lempel-Ziv Complexity for early detection of gear cracks, *in proceedings of the International Conference surveillance* **7**:100-110

[15]   Ahnaf Rashik Hassan, Mohammed Imamul Hassan Bhuiyan 2016 A decision support system for automatic sleep staging from EEG signals using tunable Q-factor wavelet transform and spectral features, *Journal of Neuroscience Methods*, **271**:107-118.

[16]   P. D. Mcfadden and J. D. Smith 1984 Model for the vibration produced by a single point defect in a rolling element bearing, *Journal of Sound and Vibration* **96**:69-82.

[17]   D. Mallikarjuna Reddy, M.Amaranth, R.Sreenidhi and S.Prabhu Swamy 2008 Experimental investigation and analysis of defects in tapered roller bearings using condition monitoring techniques, *International Journal of advances in vibration engineering*, **7**(4)