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Polymer Gear Fault Classification Using EMD-DWT Analysis Based on Combination of Entropy and Hjorth Features

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Polymer gears have proven to be an adequate replacement for traditional metal gears in various applications. They are lighter, have less inertia, and are much quieter than their metal counterparts. Polymer gears, however, are rarely employed because there is a lack of failure data. Hence, there is tremendous scope for fault detection of polymer gears. In this paper, a novel technique of polymer gear fault detection is proposed following the double decomposition of vibration signals. The experimentally acquired vibration signals are processed through two steps of decomposition, *i.e.*, empirical mode decomposition and discrete wavelet transform based Time-Frequency decomposition. Subsequently, entropy features (EF), Hjorth parameter (HP), and a combination of EF and HP are extracted. A combination of these feature sets is used to train the classifier: support vector machine (SVM), ensemble learning, and decision tree. Among all classification methods, the ensemble learning classifier reached the maximum classification accuracy of 99.2 % using a combination of EF and HP features. Furthermore, EMD and DWT are compared with the proposed double decomposition method (EMD-DWT) for accuracy validation. The experiments demonstrated that the proposed EMD-DWT method is efficient and yields promising results for classifying polymer gear faults.

Keywords: Polymer gear; EMD-DWT technique; Bagged tree; SVM; Hjorth parameter

1 Introduction

Polymer gears research has grown over the last few decades due to their low manufacturing costs and superior properties such as low density, low damping characteristics, and ability to absorb excessive vibrations.[1] Due to new developments such as material and processing in polymer gears, it can be effectively be used under severe loading conditions and at a high rotating speed.[2] Pitting, wear, root cracking, and pitch circle cracking are the most common causes of polymer gear failure.[3] However, when compared to metal gears, there are very few studies on failure detection of plastic gears. This unexpected failure in the polymer gear results in the shutdown of the machine and accidents during operation. This is the main reason behind the autonomy gear fault detection that has gained the most attention from researchers. Efficient polymer gear fault detection technique using vibration signal analysis can restrict sudden failure of the polymer gear and reduce the accident, repair cost and shut down of the machine. Thus, detecting polymer gear faults using a vibration signal is a difficult task because the vibration signal is nonlinear and non-stationary in nature. It is also affected by external noise from different parts of the machine and the damping characteristic of the polymer gear. For accurate detection of these faults, vibration signal from gears setup must be separated from external noise. However, the effectiveness of signal analysis depends on signal processing techniques. Therefore, various condition monitoring features are proposed by many authors for fault detection of gears and bearings from vibration signals analysis.[4]

In the past few years, various signal processing methods have been used in the fault detection of rotating components. The signal processing technique is broadly classified into three groups:[5] time domain, frequency domain, and time-frequency domain. The statistical properties of the signal, such as standard deviation, crest factor, root mean square (RMS), kurtosis, and so on, are important in time dependent analysis. The fast Fourier transform (FFT) algorithm is used in frequency dependent analysis to convert measured time-domain signals into the frequency domain. The study of these two methods, *i.e.*, time and frequency domain, are reliable and accurate when applied to a stationary signal. Still, for non-stationary signals, they are not very reliable.[6] To avoid these issues, A method for analyzing time and frequency

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has been developed. Previously, various literature is available based on time-frequency methods for fault detection of rotating components like gear and bearings.[7–14] The WT is a very useful method for detecting abrupt changes in non-stationary signals.[15] WT is broadly classified into two groups continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The DWT based technique is widely used to detect a fault in gears.[16–19] In recent years, several new signal processing methods for classifying gear faults are already developed and successfully implemented. For instance, Amarnath and Praveen[20] studies gear fault detection using empirical mode decomposition (EMD) based on statistical parameter analysis. In another work, Sharma and Parey[21] employed EMD with RMS-based probability density function and entropy for gear fault detection. Some scholars are focused on the failure detection of polymer gear. For example, Iba *et al*.[22] proposed a new method to cancel background vibration noise in meshing plastics gear pairs and detect gear failure using neural oscillators. Kien *et al*.[23] investigate the plastic gear fault detection using a convolution neural network. Kumar *et al*.[24] studied the polymer gear fault detection based on statistical features extracted from vibration signals.

Han *et al*. [25] investigate the combined effect of EMD, particle swarm optimization-SVM and fractal box dimension. EMD-DWT based double decomposition is a relatively new technique for signal processing and feature extraction. Although EMD-DWT analysis is mainly shown in the area of biomedical signal processing [26,27], it has not been used in the field of gear fault detection. Thus, it would be interesting to investigate the impact of the EMD-DWT domain for polymer gear fault classification. Keeping in this mind, the main aim of this study is to (i) Increase the scope of non-stationary vibration analysis for polymer gear fault detection. (ii) A comparison of the accuracy of various classifiers utilizing various feature sets for fault classification.

A categorization methodology for polymer gear signals is provided in this paper, based on features collected from the EMD, DWT, and EMD-DWT approaches. Three sets of features such as (i) Entropy feature (EF), (ii) Hjorth parameters (HP), and (iii) combination of EF and HP are used to train three different classifiers like SVM, fine Tree and bagged tree for classification of multi-class polymer gear signals. The optimal scenario for recognizing healthy and faulty polymer gear signals is produced using EMD-DWT techniques with EF and HP characteristics set for the bagged tree classifier. The results show that the best accuracy of 99.2 % is achieved.

The remaining section of this manuscript is as follows: The materials and methods are described in Section 2. Section 3 discussion about the result of this study. The final section discussed the conclusion of the study.

2 Materials and methods

2.1. Experimental setup

Figure 1 depicts the experimental setup, including an AC motor (0.75 hp) with a top speed of 2850 rpm, a variable frequency drive (VFD), a shaft, coupling, and bearings. The shaft has a diameter of 30 mm and is connected to the motor shaft via a flexible coupling. The two-roller bearing, which is located at the shaft's end, provides support for this shaft. The shaft's

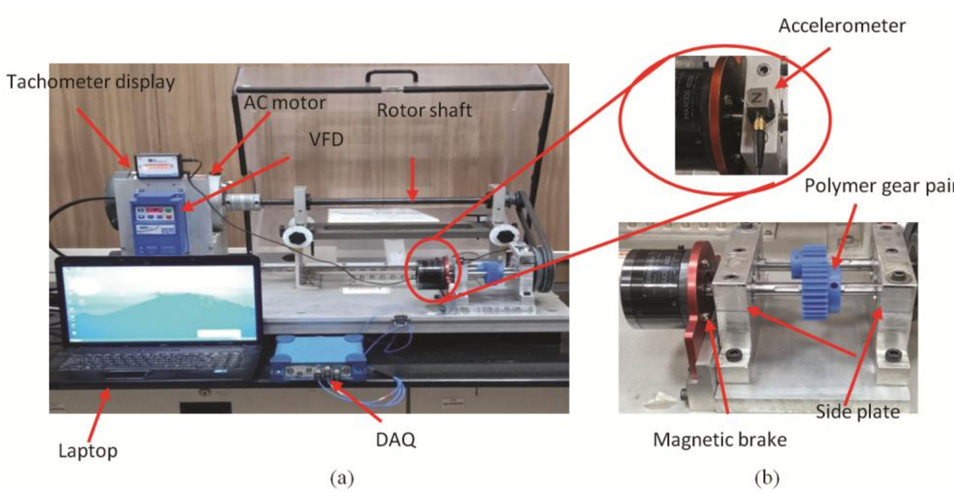

Fig 1 — (a) Machinery fault simulator, (b) Newly designed gear assembly.

motion is transmitted to the newly designed gear setup Fig.1(b) through the belt pulley arrangement. The newly designed setup consists of a base plate ($180\ mm \times 152\ mm \times 15\ mm$), side plate ($180\ mm \times 20\ mm \times 90\ mm$), bearings, shafts, and magnetic brake. The load is applied to the gear pair using a magnetic brake. The level of 3 Nm torque is applied for test conditions. A number of faults are artificially created in pinion polymer gear, and the mating polymer gear is defect-free. The vibration signal from these gears is recorded by an accelerometer positioned on the top of the side plate.

2.2. Experimental procedure

In this study, MC901 (Nylatron) polymer gear has been selected for the experiment. It is a modified group of nylon6 grade, which exhibits more stable properties than unmodified nylons. MC901 has good mechanical strength, higher flexibility, and damping properties. It is blue in color and used in bearings, gears, wheels, and custom parts. The specification of the polymer gear pair is shown in Table 1. A total of six pinion polymer gear are used in this study. One is healthy (H), and the other five are faulty with different simulated gear pitting fault classes, namely L_1, L_2, L_3, L_4, and L_5. A micro milling machine is used to create the simulated pits on the pinion gear tooth surface. It is done to keep the size within the acceptable range. The pit has a circular cross-sectional area with a diameter of 2 mm and a cylindrical depth of 0.1 mm. In fault L_1, pits are one, whereas in faults L_2, L_3, L_4, and L_5, pits with the same dimension are two, three, four, and five, respectively. The vibration signals are taken using an accelerometer mounted on a side plate. The sampling rate is 12.8 kHz, and the sample length is 10000 used for signal acquisition at all operating conditions. The raw vibration signals are recorded at four rotational frequencies, *i.e*., 10 Hz, 20 Hz, 30 Hz and 40 Hz. At each frequency, gears are operated with a load of 3 Nm torque. In this investigation, the raw vibration signals are acquired from healthy and varying levels of polymer gear defect under various testing situations.

Table 1 — Specifications of the polymer spur gear.

	Gear	Pinion
Material	MC901	MC901
Module (mm)	2	2
Pitch diameter (mm)	60	40
Tooth numbers	30	20
Pressure angle	20°	20°
Tooth depth	4.5	4.5
Tooth hardness	115-120 HRR	115-120 HRR

2.3 Features

2.3.1 Entropy features (EF)

Entropy is described as a degree of disorder of the system.[28,29] In this study, a variety of entropy parameters are used to measure the pitting fault in polymer gear, which is described as follows:

(i) **Log energy entropy** (H_{LE})

$$H_{LE} = \sum_{i=1}^{N} \log(y_i)^2 \qquad \ldots(1)$$

(ii) **Threshold entropy** (H_{Th})

$$H_{Th} = \begin{cases} 1, if\ |y_i| \rangle v, \text{and} \\ 0, \text{elsewhere} \end{cases} \qquad \ldots(2)$$

(iii) **Sure entropy** (H_{SuE})

$$H_{SuE} = N - \neq \{ i \ \ such\ \ that\ \ |y_i| \text{£} v \} + \sum_{i=1}^{N} \min\left(y_i^2, v^2\right) \qquad \ldots(3)$$

(iv) **Norm entropy** (H_{NE})

$$H_{NE} = |y_i|^{v} \qquad \ldots(4)$$

(v) **Shannon entropy (H_{SE})**

$$H_{SE} = -\sum_{i=1}^{N} y_i^2 \log\ (y_i)^2 \qquad \ldots(5)$$

Where, N is the number of samples, y_i is the coefficient of signal y, and v is the threshold.

2.3.2 Hjorth parameters (HP)

B. Hjorth[30] introduced HP, which are Activity (A), Mobility (M), and Complexity (C). HP are statistical features used in time domain signal processing as indicators. They are commonly used for feature extraction of a biomedical signal. More features necessitate more training samples, increasing computational complexity and the risk of over-fitting. To overcome this problem, HP is selected for this study. If y(t) is the vibration signal, these parameters are as follows:

(i) $$\mathrm{A} = Var\left(y(t)\right) \qquad \ldots(6)$$

(ii) $$\mathrm{M} = \sqrt{\frac{Var\left(\frac{dy(t)}{dt}\right)}{Var\left(y(t)\right)}} \qquad \ldots(7)$$

(iii) $$\mathrm{C} = \frac{M\left(\frac{dy(t)}{dt}\right)}{M\left(y(t)\right)} \qquad \ldots(8)$$

2.4 Feature extraction

This section discusses the extraction of the features described in Section 2.3 in various time-frequency domains such as EMD, DWT, and EMD-DWT.

2.4.1. Vibration signal analysis by EMD

Huang *et al*.[31] proposed the EMD based signal processing technique in 1998. It doesn't require any information about the stationary behavior of the signal or its linearity. It decomposes a signal $y(t)$ into a finite number of signals, known as its IMFs. The EMD technique and algorithm are briefly described.[32,33] According to the definition of EMD, a signal $y(t)$ is decomposed into the sum of IMFs and their residual components. It is mathematically expressed as an equation (9).

$$y(t)=\sum_{i=1}^{n} c_i(t)+r_n(t) \qquad ...(9)$$

where $c_i(t)$ symbolizes the IMFs and $r_n(t)$ is the residual component. c_1 contains high-frequency components, and the lowest frequency components lie in the last IMF. After decomposition of the signal and obtaining all the IMFs, the most dominant IMF selection is a crucial task that contains the gear information. A correlation coefficient is used to select the dominant IMF in this study. For each IMFs generated through EMD, the correlation coefficient is calculated between the raw and decomposed signal from equation (10):

$$CC=\frac{\sum_{i=1}^{N}(y_i-\bar{y})(c_i-\bar{c})}{\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2}\sqrt{\sum_{i=1}^{N}(c_i-\bar{c})^2}} \qquad ...(10)$$

In the present work, The EMD algorithm is implemented to estimate IMFs of raw vibration signals. The raw signal is decomposed into different IMF and residual. Fig. 2 & 3 illustrated IMFs after decomposition of healthy and faulty gear with L_5, respectively. After decomposition, it is important to select the dominant IMF, which includes the sensitive fault information. There are several methods developed by the researcher to choose the dominant IMF. We adopted the correlation coefficient method by equation (10) for this task.[34] Therefore, the IMF with maximum correlation coefficient value is selected as a dominant IMF. Fig. 4 depict the correlation coefficient of various IMF at 40 Hz and 3 Nm loading condition, Fig. 4 (a & b) show the correlation coefficient of Healthy and faulty gear (L_5), respectively. We have extracted entropy features and Hjorth parameters from IMF1. Thus, we have a total of 8 features extracted in the EMD domain.

2.4.2 Vibration signal analysis by DWT

In the wavelet process, the time domain signal is converted into a wavelet domain with the help of the mother wavelet. A wavelet function explain as:[35]

$$\psi_{m,n}(t)=\frac{1}{\sqrt{m}}\psi\left(\frac{t-n}{m}\right)\ \left(n\in IR,\ m\in IR_{+}^{*}\right) \qquad ...(11)$$

Where m denotes the scale and n indicates the shift factor. The signal is decomposed into an approximation and detailed coefficients using a DWT-based method in this study. DWT has a wide range of mathematics, science, and engineering applications. DWT method works on sub-band coding and requires less computation time for the wavelet

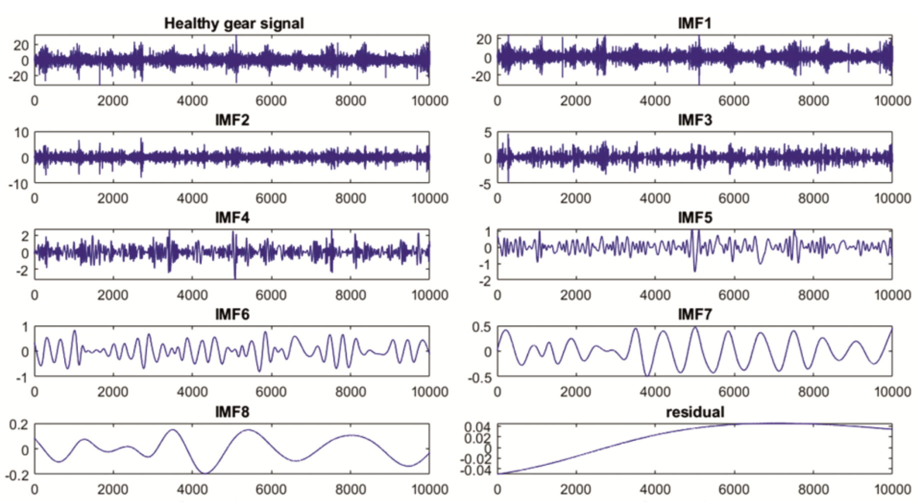

Fig. 2 — Healthy gear signal and IMFs at 40 Hz, 3 Nm.

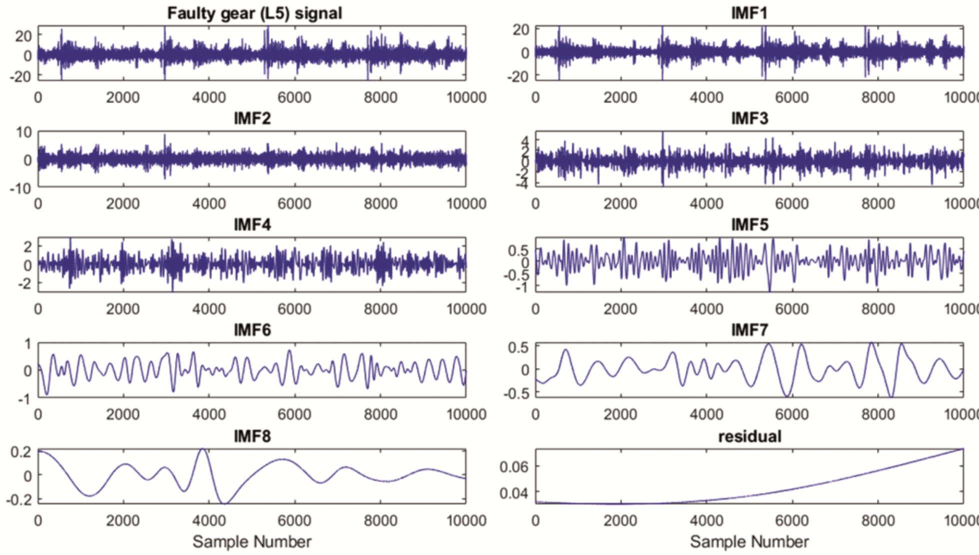

Fig. 3 — L_5 fault gear signal and IMFs at 40 Hz, 3Nm.

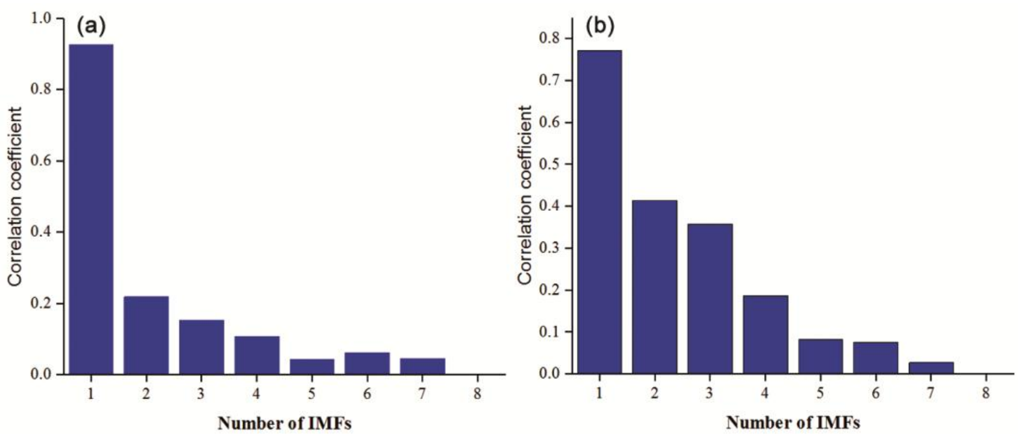

Fig. 4 — Correlation coefficient comparison of IMFs. (a) Healthy gear at 40 Hz, (b) L_5 gear at 40 Hz.

transform. The mathematical equation for defining the DWT is as:

$$W_{j,k} = \sum_{j} \sum_{k} x(k) 2^{-j/2} \psi\left(2^{-j} n - k\right) \qquad ...(12)$$

The accuracy of wavelet analysis can be analyzed by using the appropriate filter for a specific case. Daubechies wavelets are used in this study because of their orthogonality, low computational effort, and compact time-domain support.[36] To extract features by the DWT method, a 6 level decomposition of the raw vibration signal is carried out using Daubechies-4 (db4) as the mother wavelet. The details coefficient level 1 is used for feature extraction because it holds the most sensitive information, *i.e.*, maximum energy ratio. Thus, we have a total of 8 features extracted in the DWT domain.

2.4.3 Vibration signal analysis by EMD-DWT methods

This section decomposes raw vibration signal using EMD and dominant IMF, *i.e.*, IMF 1 is then decomposed into DWT. Debaucheries 4 mother wavelet is used to decompose the 1st IMF (dominant IMF) into details and approximation coefficient up to six decomposition levels. After that, the authors select a decomposed signal that holds the sensitive fault information and reduces the computational time for further analysis of the decomposed signal. It observed that level 1 of decomposed signal belongs to higher frequency categories. It holds sensitive fault data of polymer gear system, which is investigated and supported by calculating the energy ratio of all decomposed levels.[37]. Decomposition level 1 has found a maximum energy ratio; therefore, level 1 is used for fault feature extraction. Thus, we have eight features extracted in the EMD-DWT domain, and these features are fed into the various classifier.

2.5. Classification

In this study, three sets of features, such as EF, HP, and EF+HP, are used separately to detect the polymer gear classification using three different machine learning techniques, *i.e*., bagged tree, decision tree, and support vector machine (SVM).

2.5.1. Ensemble learning method (Bagged Tree)

In the bagging technique, the main aim is to create several subsets of data chosen randomly from the training sample. Each collection of the subset data is fed to train the respective decision tree. The decision trees are derived by constructing the base classifiers B_1, B_2, B_3,…., B_n with the bootstrap samples J_1, J_2, J_3, …., Jn, respectively, by replacement from the defined data set J. The resulting bagged tree model consists of a grouping of all the constructed base classifiers and the majority's votes. Thus, the ensemble model results in the mean of predictions from different decision trees and is noticeably more vigorous than a single decision tree. When tuning the parameters of a Bagged tree in this study, the maximum number of splits and number of learners were set to 239 and 30, respectively.

2.5.2. Decision trees classifier

It is a family of supervised machine learning algorithms. The decision tree is a tree-shaped classifier used to determine a course of action. In this classifier, the decision node and leaf node are two significant parts. The decision node has multiple branches, and it is used to form a possible decision. Leaf nodes do not have any components and give an output of decision. In this algorithm, the selection of splits is the most crucial element.[38] In this study, the fine tree method is used with a maximum number of the split is 100 and Gini's diversity index is used for the split criterion.

2.5.3. Support vector machine (SVM)

SVM belongs to the supervised learning classification. Its main aim is to obtain an optimal hyperplane in a space (number of features) such that separation between two classes is maximum. The SVM technique is details described.[39] A quadratic linear-based SVM with a box constraint level 1, kernel scale mode "auto," and multiple class method "one-vs-one" is considered in this study. Quadratic SVM takes roughly 60 seconds to train.

3 Results and discussion

This section contains the findings of feature analysis and classification are presented. The classification methods such as SVM, fine tree and bagged tree are trained using the 10-fold cross-validation method. For ten-fold cross-validation, the processes will be repeated ten times, with one subset out of ten being used for training each time. This approach is preferred because it avoids any possibility of statistical biases for dividing data.[29] Table 2- 4 shows the accuracy of different features set with different classifiers for EMD-DWT, EMD and DWT method, respectively. Table 2 shows the performance of the different combination features extracted from the EMD-DWT approach with different classifiers. Three sets of features are used, known as EF, HP and a combination of EF and HP as a feature vector for different classifiers. Observing the performance from Table 2, the combination of EF and HP feature vector with bagged tree produces the highest accuracy of 99.2%. However, the classification accuracy performance of fine tree and SVM is 90% and 84.6%, respectively.

Table 3 shows the performance of the different combination features extracted from the EMD approach with different classifiers. The outcomes from Table 2, the combination of EF and HP feature vector with bagged tree produces the accuracy of 97.5%. However, the classification accuracy performance of fine tree and SVM is 88.3 and 75%, respectively. Table 4 shows the performance of the different combination features extracted from the DWT approach with different classifiers. The classification accuracy of the bagged tree, fine tree and SVM for DWT using combined features EF+HP is 97.9%, 88.8% and 71.7 %, respectively, as shown in Table 4. Here, it is also observed that the achieved

Table 2 — Comparison of the accuracy of three different machine learning techniques with EMD-DWT.

Machine learning technique	Accuracy (%)		
	EF	HP	EF and HP
Bagged Tree	89.6	93.3	99.2
Fine Tree	90	85.8	90
SVM	35.8	65	84.6

Table 3 — Comparison of the accuracy of three different machine learning techniques with EMD.

Machine learning technique	Accuracy (%)		
	EF	HP	EF and HP
Bagged Tree	90	92.5	97.5
Fine Tree	85.4	88.8	88.3
SVM	26.2	62.5	75

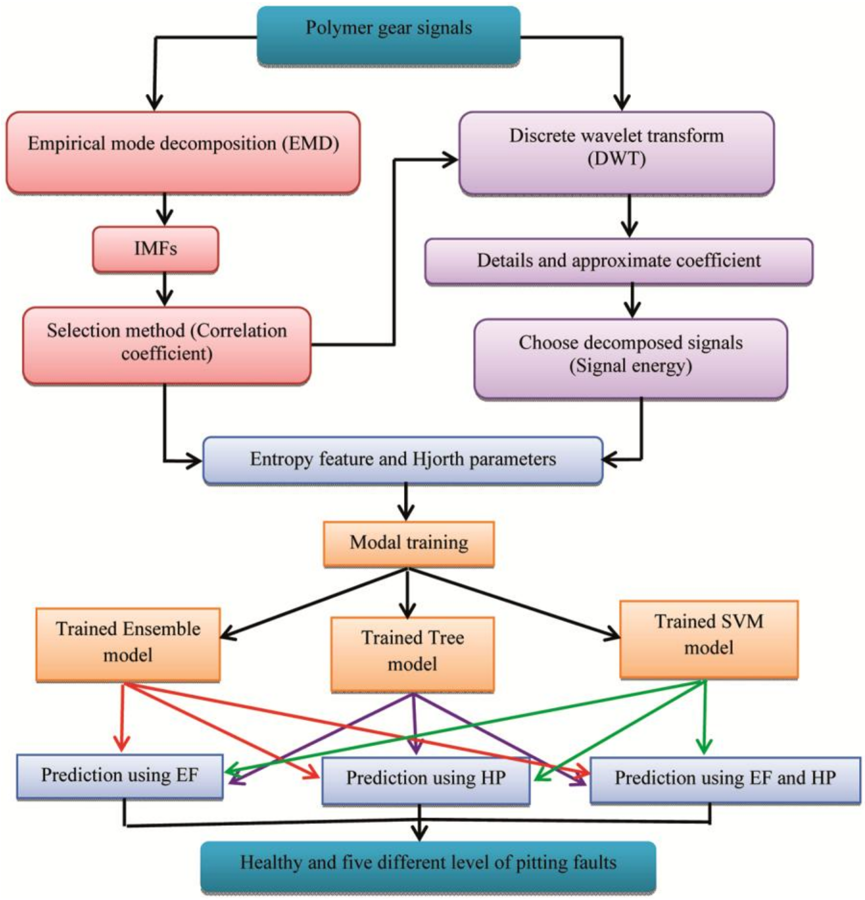

Fig. 5 — The Flowchart of the developed model for the fault classification of polymer gear. EF stands for entropy feature, and HP stands for Hjorth parameters.

Table 4 — Comparison of the accuracy of three different machine learning techniques with DWT.

Machine learning technique	Accuracy (%)		
	EF	HP	EF and HP
Bagged Tree	92.9	92.5	97.9
Fine Tree	87.9	92.1	88.8
SVM	35.4	56.7	71.7

Table 5 — Confusion matrix of bagged tree classifier using combined EF and HP by EMD-DWT.

H	L_1	L_2	L_3	L_4	L_5	Classified as
40	0	0	0	0	0	H
0	40	0	0	0	0	L_1
0	0	40	0	0	0	L_2
0	0	0	40	0	0	L_3
0	0	0	0	40	0	L_4
1	0	0	0	0	39	L_5

classification accuracy is higher when using the combination of EF and HP feature sets compared to EF and HP separately. Table 5 shows the confusion matrix of the bagged tree classifier, considering the combined EF and HP feature set extracted from EMD-DWT. The high accuracy of the proposed method indicates that it may be helpful in the fault detection of polymer gear. Hence, the proposed methodology may be able to classify polymer gear faults. The method adopted in this study for extraction features and classification of polymer gear faults is summarized in Fig. 5.

4 Conclusion

This research aims to develop the EMD-DWT based double decomposition technique for polymer gear fault detection. The proposed method identifies the different levels of pitting fault in polymer gear. For this purpose, three sets of features, *i.e.*, EF, HP and combined EF and HP feature set, are extracted in EMD, DWT and EMD-DWT approach. Three classifiers are used to classify the fault and compare the accuracy with different features set. The combined features set, *i.e.*, EF and HP extracted from the EMD-DWT approach combined with a bagged tree, show the highest classification accuracy. The proposed method's performance is also compared to EMD and

DWT separately. The results indicate that the proposed feature extraction methodology can identify polymer gear faults with a minimum number of features.

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