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VIBRATION SIGNATURE ANALYSIS BY HYBRID MULTI-LAYER NEURO-FUZZY SYSTEM

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Abstract: A proficient fault detection model has to be sketched for detecting slight variations of the vibrating signal of rotating machine whereas the diagnosis process prominently stuck with the inefficient extraction of effectual features of a signal in reduced time. Existence of above stated issue results in the confinement of inventive Module 1 of the Vibration Signature Analysis by Hybrid Multi-Layer Neuro – Fuzzy System (V-HMNFS), which could collect the RKC (RMS, Kurtosis, Crest factor) signal features for every instantaneous signal unit while eliminates noise thereby reducing pre-processing task. This in turn lessens time consumption and at the end yields learnt extracted faulty features. Accurate classification of faulty features can be accomplished by casting inimitable Module 2 classifier which provokes a good path to provide accurate classification based on learnt features. This responsible classifier collectively organises the RKC features of respective signal units and does accurate classification of faulty occurrences based on the features in less time.

Keywords: V-HMNFS; RMS; crest factor; Kurtosis; feature extraction; RKC.

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1. INTRODUCTION

One of the most significant parts of rotating machines are Rolling bearings, thus conditioned monitoring of rotating machine prevent the failure of machine [1]. When faults are generated in the rotating bearing, it causes vibration and noise, which will make the machine breakdown/shutdown [2]. In industrial perspective production of product vacant, sometime severe vibrations of bearings can even lead the whole system to operate incorrectly [3]. To overcome these issues there are several monitoring ways accessible, that need costly sensors and specialised tools.

This resulted the necessity for a less expensive and precise technique for identifying and preventing the machine faults rather than curing issues. Effective and economical fault diagnosing to prevent machine fault is usually a difficult task due to large process involved like data acquisition, feature extraction, and fault detection and identification structure [4]. In order to prolong life of bearings, it becomes pertinent to develop a consistent system to predict faults in bearings which may help in easing the three problems mentioned above.

There are several different bearing fault prediction techniques, one of the foremost popularly used algorithm is 'Vibration Signal Analysis'. It is long since understood that vibration signals and sound/acoustic signal from rotating machines are connected with their structural dynamics [5]. Dominant diagnostic information can be attained from non-healthy vibration signals from rotating parts by using appropriate process technique. In recent years, varied fault detection ways are projected and developed in hand with vibration signal analysis like blind source separation [6], wavelet transform [7–9] and empirical mode decomposition [10–12] for fault detection and diagnosing of mechanical systems.

These ways type the idea of most applications today, as they provide the chance of time-frequency analysis of signals. Converging need for time frequency analysis, the thought of instantaneous frequency may be determined for each time purpose, making it potential to have a deeper investigation on feature analysis in offset phenomena [13]. This extraction is achieved by Empirical Mode Decomposition (EMD). Most commonly, EMD and Fuzzy Entropy (FE) have

been implemented for extracting the useful features from the vibration signals taken as input. Also for the fault diagnosis, BPNN is implemented [14].

This neural network concept lead the grouping of SOMNN with PCA for the purpose of fault diagnosing [15]. The stuck in inefficient feature extraction by PCA brought wavelet entropy along with SVM [16]. The time complexity in SVM build Deep learning [17] which is one of the strongest representational learning algorithms and DBNs [18, 19] are experts in constructing deep-belief structures.

Deep Belief Nets are thought of as an awfully intricate non-linear feature extraction algorithms, in this all hidden layers learn to characterise required features which are useful and that attain higher order associations in the originally collected input data set. Recently developed applications of DBNs are: hand-written character recognition [20], speech recognition [21], 3D-object recognition [22], and extraction of road maps from clustered-aerial images [23] as well as knowledge retrieval [24]. The maintenance department is to inherit the best from above requisites and stay rotating machinery and plant equipment in smart operative condition that prevents failure and production loss.

Monitoring the rotating machine has been a difficult task for engineers particularly in industries because the vibration signals emitted by rotating parts of machinery have a non-stationary characteristic but the actual signal are weak and possess low energy generated by the faulty components, but with sturdy noise. This necessitate the effective extraction of features for diagnosis which represents main fault information of vibration signals in least time. Though effective extractions of features are made success for each and every instantaneous frequency, there arises a need to predict accurately the fault by precise collection of all the features in less time. Henceforth a proficient algorithm is presented in the proposed methodology section.

2. PROPOSED FEATURE EXTRACTION AND CLASSIFICATION ALGORITHMS: V-HMNFS

Fault detection is a vital process in analysis of vibrational signal yielded from rotating machinery. Vibration signals have to be analysed in depth for that there is an increased need to

extract the features such as RMS, Kurtosis and Crest factor from every signal unit whereas obtaining features from each individual unit is more tedious. To analyse all such aspects, here we propose a system consisting of two modules: first, which has the stochastic nature to accurately extract the required features based on the characteristics for feature extraction which considers every signal unit and the second, for an efficient fault diagnosis process where there is an increased need to exactly classify faulty signals in reduced time. In the first module, the effectual features are accurately obtained by the aid of Hilbert Huang Transform which utilizes EMD (Empirical Mode Decomposition) for effective IMF (Intrinsic Mode Function) extraction. The features are learned individually based on the faulty features using DBN which at end yields the learned faulty features. In the second module of the proposed system, the classifier utilizes the random forest algorithm which makes a list of available outputs. The problem of overfitting in RF is tackled by the ANFIS which utilizes the knowledge based rule for prediction.

The techniques used are explained and the overall proposed architecture described below.

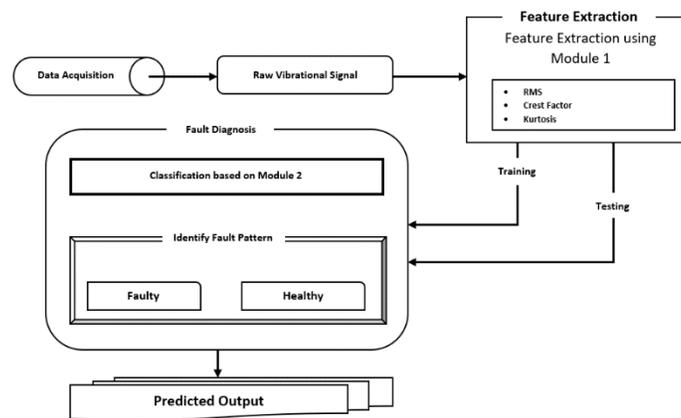


Figure 1. V-HMNFS for Fault Diagnosis

This proposed architecture show V-HMNF System for feature extraction and Fault Diagnosis which aims at improving automatic identification of faults accurately. One of the primary requirements for this system to work is the availability of vibration signals from a healthy machine of the same species. We are interested in accurate fault prediction as part of Condition Based Monitoring (CBM), hence we have considered Vibration Signature (VS). In our proposal, the

system starts with collection of raw data emitted by machines from appropriate rotating machine parts by various data acquisition methods. This raw vibration data is mostly very noisy and is also exposed to numerous environmental impurities. In order to detect features effectively identifying and eradicating noise, the first module was developed. This feature extraction technique automatically pre-processed the raw data with the help of high speed training and utilizes the advantage of DBN thereby concentrating on the extraction of only required RKC features. The first module determines the features of the original signal for every instantaneous frequency irrespective of signal type by the greedy layer wise learning enabling fast and active sorts without redundancy and noise. Every signal's RKC features are determined and learnt which holds the faulty signal information. After this process in order to detect the fault diagnosis automatically, an intelligent pattern classification method is introduced as the second module. Finally faulty and healthy or VS feature are compared which is based on the pattern matching concept and the predicted output is finally retrieved.

2.1. DATA ACQUISITION

Fault Diagnosis starts with data acquisition, where machine individualities are captured for further analyses and our work is focused on vibration signature based fault prediction as discussed in eqn (1)

$$V_i(t) = \{V_1(t), V_2(t), \dots, V_m(t)\} \quad (1)$$

Let $V_i(t)$ is the set of data of original vibration signal from various mechanical components of the machine. Any required feature of a rotating machinery can easily be calculated from the raw vibration signal data, however the data needs to be pre-processed. But in this work the raw data is automatically pre-processed with the help of our proposed feature extraction technique.

2.2. MODULE 1 FOR FEATURE SELECTION

Initially vibration data are sent to the feature extraction phase for removal of vibration noise and accurate extraction of proposed features. In order to extract the accurate features we have proposed the Module 1 which is based on the inspiration of the accurate selective separation of required elements. Here the required features are RKC and the selection process is done by

utilizing EMD based Hilber Haung Transform (HHT) implemented on Deep Belief Networks (DBN).

The Module 1 pre-training procedure treats each consecutive pair of layers in the learning process, whose joint probability is defined as,

$$J_{h,u}(h,v) = \frac{1}{p(\omega)_{h,v}} .e^{(V_i(t)wh+v^T b+a^T h)} \quad (2)$$

The above eqn (1) describes the RBM (Restricted Boltzmann Machine) that has deep learning nature which constituted in each layer h and constitutes the primal DBN structure $p(\omega)_{h,v}$, then backward adjustment is applied to continuous variable v. DBN uses labelled data to train the conditional probability $J_{h,u}(h,u)$ which has the same form as that in DBN layer, and the error range from top to bottom in order to adjust the network. The output value of the DBN output layer vis-a-vis the original value, it gives the error value resulting due to the applied weight. This error value is then calculated backwards to obtain the error precipitated by each layer, thus the efficient weight calculation to extract the fault feature is complete. Now it is necessary to calculate weight with proper bias b to mitigate the training error which is given in

$$J_{h,u}(h,v) = \frac{1}{p(\omega)_{h,u}} .e^{(V(t) wh+(v-b)^T (v-b)+a^T h)} \quad (3)$$

The RBM parameters can be efficiently trained in an unsupervised fashion by maximizing the likelihood of the joint probability in equation (2)

$$L = \prod_t \sum_h J_{h,u}(h,v(t)) \quad (4)$$

This L is over training samples of vibrated signal $v(t)$.

For extracting the IMFs of a complex (vibration plus acoustic) signal in feature extraction, the training phase of Module 1 algorithm adopts the EMD technique to determine the mono-component of the original vibration raw signal.

EMD can efficiently decompose any given signal into its individual mono-component

signals called Intrinsic-Mode Function (IMF). An IMF must satisfy two conditions given below:

1. In the considered data set, the difference between the number of extrema and the number of zero-crossings must be 0 or at max 1, and
2. At any instance of time, the mean value of the envelope defined by local maxima and the local minima is zero.

The instantaneous mono-component signal, IMF is obtained in order to analyse the signal individually for better confinement of effectual features from each unit which is obtained by EMD methodology [25]. Post EMD, a signal $V(t)$ for eqn (2) is expressed as eqn (4),

$$V(t) = \sum_{i=1}^n x_i + y_n \quad (5)$$

Where x_i is the i^{th} decomposed IMF of the signal $V(t)$, y_n is the noisy signal. Here the EMD determines the mono-component of the original signal individually but there is an extended need to analyse every mono-component individually based on its instantaneous frequency, so that the effectual features can be obtained from each individual vibration signal and also in addition this EMD process results in some limited amount of noise, which must also be handled. Above stated issues are handled by obtaining the Hilbert Haung transform which results in a selective pre-processing of the effectual signal features obtained. Here HHT is implemented on both sides of Eqn(5), the Hilbert-Haung spectrum of $V(t)$, $P(\omega, t)$, is obtained from the following equation (6):

$$P(\omega, t) = \text{Re}_e \sum_{i=1}^n v_i(t) e^{j \int \omega_i(t) dt} \quad (6)$$

Where ' Re_e ' is the operator of real part, $v_i(t)$ is the function of the amplitude and $\omega_i(t)$ denotes the function of the instantaneous frequency. It is notable that the residual value y_n in Eqn (5), which uses very small amount of energy from the signal, is ignored; thus noise is avoided, which is equivalent to pre-processing of the signal by utilizing eqn (6), which in turn reduces the time factor for extraction of faulty features.

The marginal spectrum of HHT which extracts RKC features is expressed by an integrated

spectrum w.r.t. time as in eqn (7)

$$p(\omega) = \int_0^T P(\omega, t_{(RMS, Crest\ Factor, Kurtosis)}) dt \quad (7)$$

where T is number of the features of $V(t)$ and $P(\omega, t)$ can exactly describe the extraction of effectual faulty feature such as RMS, Kurtosis, and Crest of every individual IMF mono-component with defined time interval. The advantage of our extraction technique with the help of HHT is to obtain all feature extracted within instantaneous frequency limit without noise existence.

Such that calculating IMF and Residue using Module 1, the machine noises are eradicated and raw data are conditioned automatically with the help of Module 1 Training. Thus on the whole, feature Extraction by Module 1 is the process of precisely extracting required features of the faulty signal from the raw vibrated signal. The overall architecture of Module 1 is described below fig 2

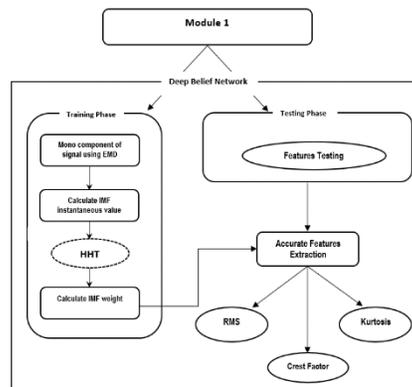


Figure 2. Module 1 Schematic Architecture

Normally, the factors such as RMS, Kurtosis, and Crest factor are seen to be prominently projected criteria of a faulty signal when compared with normal vibrated signals. Therefore, by analysing the RKC features it is easier for knocking out of the faulty signals without random searching which is the reason for deeply learning the three parameters R,K & C. This RKC interprets as the key to judge the existing faulty signals. The description of RKC Features are given below:

(i) RMS value: The Root Mean Square(RMS) value of any EM, acoustic or vibration signal is a feature which is based on time-line analysis. It is the measure of strength or power content in

the signal. RMS is effective for tracking the overall contamination level; however it doesn't provide any details on which machine part is breaking down. Mis-alignments on the rotating parts are very accurately identified with the help of RMS. RMS of a trained data series, $v(t)$, over 1 to n .

$$RMS = \sqrt{\frac{1}{N} \times \sum_{n=1}^n v(t)_n^2} \quad (8)$$

(ii) Kurtosis : Kurtosis is defined as the distribution plus measure of the comparative peakiness/ flatness of any distribution vis -a-vis a normal distribution. This important feature provides an idea of the size of the tails of distribution. It is widely used as an indicator to significant peaks in a given set of data. As a gear in use gradually wears and chips away, Kurtosis would signal an error due to the augmented level of vibration from the machine.

$$Kurtosis = \frac{\sum_{n=1}^N [v(t) - \mu]^4}{N \times (\sigma^2)^2} \quad (9)$$

such that $v(t)$ is the raw time series at point n ,

μ is the mean of the trained data, σ^2 is the variance of the data, N is the total number of data points.

(iii) Crest Factor : Crest Factor is a better and more useful feature and is defined as the ratio of the peak value of the input signal to the RMS value. Thus, peaks in the time series signal give a proportionate increase in the crest factor value.

$$Crestfactor = \frac{Peak\ Level}{RMS} \quad (10)$$

Finally features are extracted perfectly without noise and redundancy. The main advantage of our proposed feature extraction technique is the adaptability to all kinds of signals due to the joint probability distribution parameter of RBM. After obtaining features, the useful features extracted here need a pattern classification algorithm for automatic fault diagnosis. In this work, Module 2 is proposed for the purpose by grouping all those extracted mono-component features which is achieved by the predictable ensemble nature of the following classifier.

2.3 FAULT DIAGNOSIS USING MODULE 2

The elimination classification is carried out in Module 2. In our work this classifier offers

deep learning or searching by means of the randomized character of Random forest (RF) and predictive function by means of ANFIS having knowledge based prior judging. Thus, once the learnt faulty features are fed to this classifier which analyzes deeply and offers accurate diagnosis which in turn separates the classified faulty signals.

Initially, the output results L_i (1) and L_i (2) of the trained Module 1 should be fed into the Module 2 classifier which offers deep learning by means of RF . The data fusion training of the faulty features is defined as

$$\left[\begin{array}{l} \circ(1) \\ i \quad \text{arg}_i \max L_i^{(1)} = \text{arg}_i \max p(\omega_i) \\ \circ(2) \\ i \quad \text{arg}_i \max L_i^{(2)} = \text{arg}_i \max p(\omega_i) \end{array} \right] \quad (11)$$

Where $i=1,2,3,\dots,m$,

$$\text{where } [p(\omega_i) = p(\omega_1) + p(\omega_2) + \dots + p(\omega_m)] \quad (12)$$

The Learning Features $L_i(p(\omega_i))$ is imported from eqn 6 that consist of RKC ,which is utilized for diagnosing the fault.

$$L_i = [L_1^{(1)}, L_2^{(2)}, \dots, L_m^k] \quad (13)$$

The above eqn (12) is used to construct a tree with different bootstrap sample from original data using a tree classification algorithm. Where 'm' is the number of features which are extracted from Module 1. After the forest is formed, object that needs to be trained is put down under each of the trees in the forest for training. The training features are described in the eqn (13)

$$\omega_i = L_i \max p(\omega_i) \quad (14)$$

Next, the accurate prediction process of the Module 2 classifier post deep learning is done by utilizing the Neuro-fuzzy inference system which utilizes knowledge based pattern identification for the prediction of vibration fault signal.

It is well observed that ANFIS modelling is better organized plus less dependent on expert knowledge. This makes it more objective. For the purpose of generality as well as simplicity, it may be considered that the ANFIS in this work has 2 inputs, x and y and 1 output f.

Here we assume that the considered rule base consists of only 2 ‘if–then’ rules of 1st order Sugeno type, then the given ANFIS structure is discussed using the following example:

Rule 1: If a is P₁ and b is Q₁, then f₁ = x₁ a + y₁ b + r₁, (15)

Rule 2: If a is P₂ and b is Q₂, then f₂ = x₂ a + y₂ b + r₂ (16)

where a and b are the inputs, P₁, P₂, Q₁ and Q₂ are fuzzy sets which represents the range of the RKC features that are determined during the training process, x₁, y₁, r₁, x₂, y₂ and r₂ are design parameters that are also determined during the training process and the Module 2 structure is shown in the next Fig 3

$$\text{overall output} = \sum \omega_i f_i = \frac{\sum \omega_i f_i}{\sum \omega_i} \tag{17}$$

The above algorithm is an amalgamation of the Gradient Descent(GD) method as well as Least Squares Estimate(LSE) which consists of 2 steps:-

First step is that, the premise parameters are presumed to be constant while the optimal consequent parameters are subsequently identified by LSE.

Second step is that, the consequent parameters are presumed to be constant while the premise parameters are improvised by Back-Propagation GD method based on the error values, thus yielding the optimized classification by pointing the correct prediction.

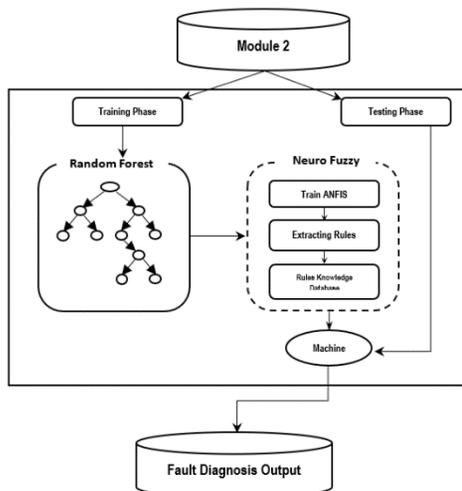


Figure 3. Module 2 for Classification and Fault Diagnosis

Finally the precise diagnosis of the behaviour of rotating machine faults is identified in fast prediction time without noise redundancy.

Thus, by the usage of efficient feature extraction by utilizing Module 1 and the intelligent pattern recognition by means of Module 2 classifier, the V-HMNF System correctly classifies fault with the assistance of learning based feature extraction. This is the well-lit process, where due to the expelling of pre-processing stage and accurate prediction process, there is optimal use of time. The result validation in the below section will be an added proof for the efficiency of the work.

3. RESULT AND DISCUSSION

Our proposed system has been described in detail in the preceding section. In the results section, we discuss in detail about its performance and the actual analysis. Our proposed system is implemented in MATLAB 2015a, which requires Windows 10 and minimum 8 GB RAM.

3.1 DATA COLLECTION

We collected the Data set from ‘a single-stage reciprocating-type air compressor’ installed at the Department of Electrical and Electronics Engineering Laboratory. Following are the Specifications of the machine:

1. Required Air Pressure Range upto 500lb/m² and 0 to 35 Kg/cm²
2. 5 HP Induction Motor with 415 V and 5 Amp, 50 Hz, 1440 rpm
3. PR- 15 Type Pressure Switch having Range 100 to 213 PSI

Data set comprises of the following states: 01 healthy state and 07 faulty states:- Leakage-Inlet Valve(LIV) fault, Leakage-Outlet Valve(LOV) fault, Non-Return Valve(NRV) fault, Piston-ring fault, Fly-wheel fault, Rider-belt fault, and Bearing fault. In order to obtain recordings/ instances of data from all the above mentioned states, faults were intentionally sowed into the air compressor.

3.2 SIMULATION RESULT

The vibrated bearing fault raw dataset are plotted in the given below fig 4 and the histogram figures are plotted in the figure 5.

VIBRATION SIGNATURE ANALYSIS

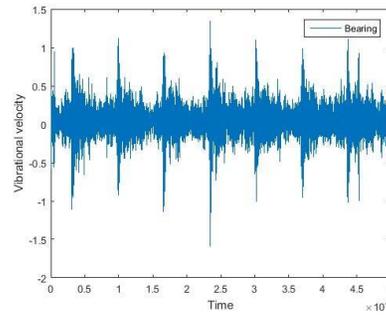


Figure 4. Original Raw Bearing Vibrated Signal of Bearing

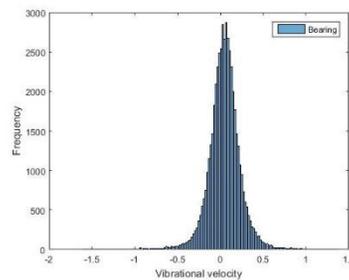


Figure 5. Histogram of Raw Vibrated Signal of Bearing

The vibrated signal is focusing on the feature extraction like RMS, kurtosis, Crest factor. In this paper, Module 1 is utilized for accurate extraction of features. EMD determines the mono-component of original signal Our proposed intrinsic mode function of the original signal is described in fig 6,7 and 8.

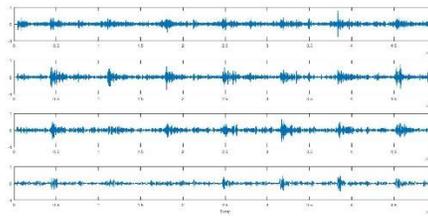


Figure 6. IMF 1 Values of Original Signal

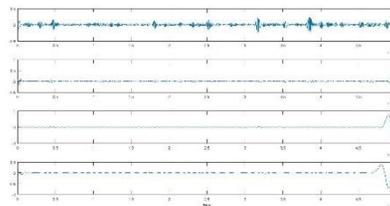


Figure 7. IMF 2 Values of Original Signal

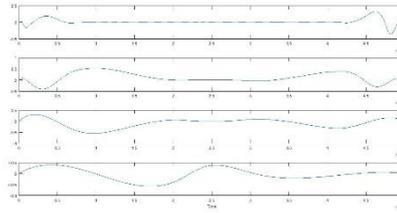


Figure 8. IMF 3 Values of Original Signal

After EMD technique the instantaneous frequency is calculated using Hilbert Huang Transform. In this below figure 9 shows that the spectrogram of HHT of instantaneous frequency signal

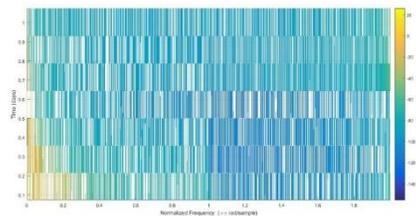


Figure 9. EMD based Hilbert-Huang Transform

After that process some faulty signal are available in the above information. In order to avoid this issue Module 1 is utilized for deep learning. The learning behavior of Module 1 is used to extract the required features for fault diagnosis in precise way with the help of IMF calculation which is widely used mono-component of individual frequency signal. Finally, precise noise features are eliminated and our required features such as RKC are accurately extracted within the less time. After this process our proposed feature extraction are described in the below fig 10,11,12.

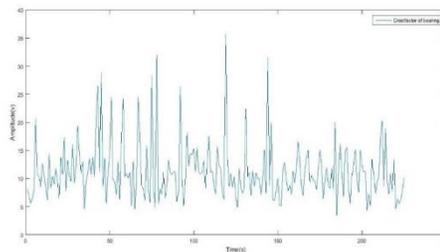


Figure 10. Crest factor of Bearing

VIBRATION SIGNATURE ANALYSIS

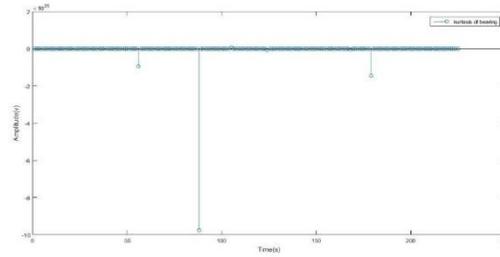


Figure 11. Kurtosis of Bearing

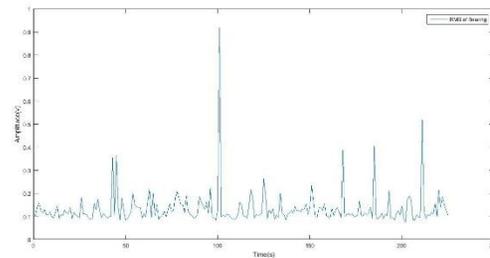


Figure 12. RMS of Bearing

In order to predict the accurate vibrated signal, intelligent pattern classification is required, so in this research paper focuses on Module 2 for classification and prediction of the accurate faulty signal automatically. The Figure 13 given below describes the decision tree but it doesn't predict the accurate signal because it has apriori knowledge less nature

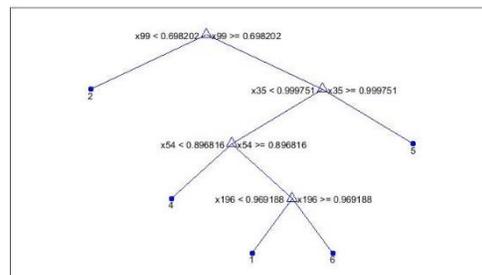


Figure 13. Random Forest Decision Tree

Next, in order to predict the accurate vibration signal, neuro fuzzy enzymes are proposed to classify the accurate vibration faulty signal. The Figure 15 given below describes the decision tree after Random forest prediction using proposed randomized neuro fuzzy enzymes.

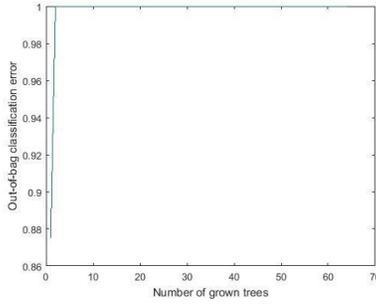


Figure 14. Error of Prediction in RF

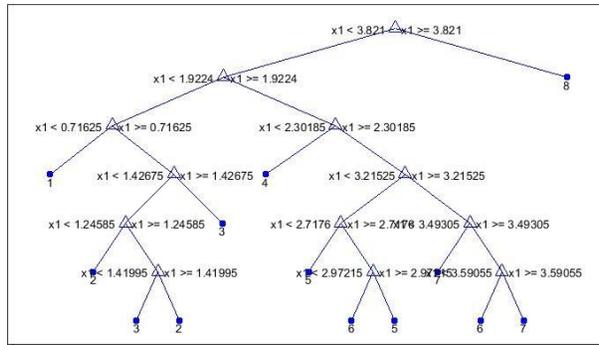


Figure 15. Module 2 Algorithm Decision Tree

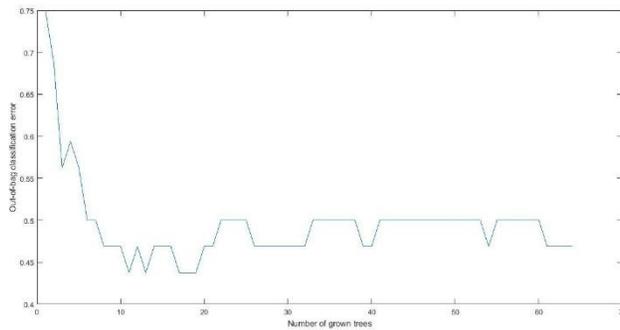


Figure 16. Proposed Accurate Faulty Signal Detection Based on Decision Tree

Figure 16 given above describes the faulty signal detection in the Non-linear Non-stationary rotating machine using Module 2 Classifier. Finally the accurate behaviour of faulty state is identified in the best possible manner. Our proposed algorithm has knowledge based automatic detection for diagnosing the faulty signal.

3.3 COMPARISON ANALYSIS

Comparison was made by proper analysis of computation time, accuracy, Diagnosis

Accuracy, Testing Prediction Time and Diagnosis Noise are described below section.

3.4 COMPUTATION TIME

Computation time during feature extraction is defined as the time required for extracting the necessary features from raw vibration data. The computation formulas are described below.

$$Computation\ Time = Starting\ Time\ of\ feature\ extraction - Ending\ Time\ of\ feature\ extraction \quad (17)$$

Table 1: Computation Time Of Proposed Transform And Existing Transforms

S.no	Algorithm	Run Time
1	TDSP	0.034
2	Fast flourier Transform	0.013
3	Morlet wave let Transform	0.072
4	Discrete wave let transform	0.092
5	Short time Fourier transform	0.648
6	Wigner wile Distribution	0.008
7	Pseudo- Wigner Wille Distribution	2.120
8	Auto correlation	0.028
9	Updated more let Transform	0.029
10	Convolution with sine	0.012
11	S-transform	5.328
12	Proposed	0.021

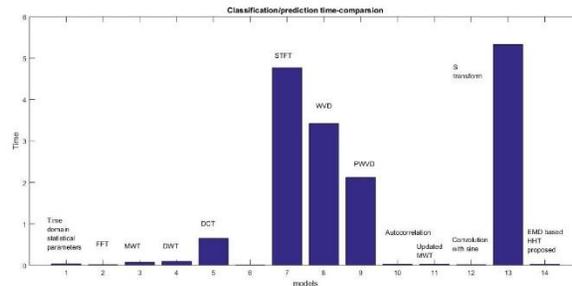


Figure 17. Comparison of Proposed and Existing Transform for Feature Extraction

Figure 17 exhibits the average run time per individual instance of the data set for execution of each transform. The average of run times of over 1000 instances of algorithm execution describes the run time for popular transforms used for analysing the selected features, e.g. FFT and STFT, etc.. The values are described in table 1 and our proposed feature extraction which utilize training with EDM based HHT attain the lower computation time when compared to existing works.

3.5 ACCURACY

The ability to differentiate between the faulty and healthy condition is the Accuracy of any algorithm test. It is actually the proportion of true positive vis-a-vis true negative in all considered cases.

$$Accuracy = \frac{a+d}{a+d+c+b} \quad (18)$$

Where,

True positive(a) = the no. of features correctly identified as faults,

False positive(c) = the no. of features incorrectly identified as faults,

True negative(d) = the no. of features correctly identified as Normal,

False negative(b) = the no. of features incorrectly identified as Normal.

Table 2: Accuracy Comparison of Various Bearing and Proposed Bearing

S.no	Algorithm	Total (sec)
1	KNN	86.67
2	PNN	90
3	RBN	96.67
4	PSO-SVM	96.67
5	PROPOSED	98.2

VIBRATION SIGNATURE ANALYSIS

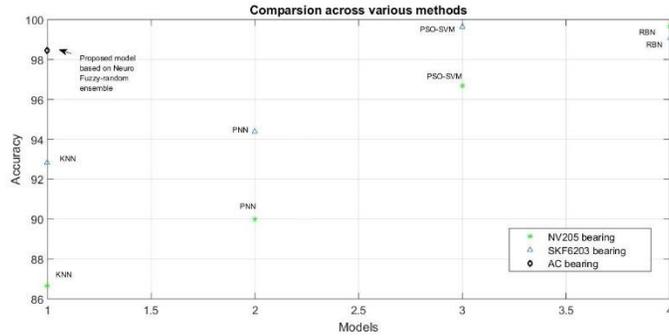


Figure 18. Accuracy Comparison for Various Existing Bearing Method and Proposed

Figure 18 depicts the Accuracy prediction time per instance of data set for executing each transform and its relative fault diagnosis, which describes the accuracy for existing and analysing the diagnosing the fault, those using KNN, PNN, RBN, PSO-SVM, and proposed the values are described in table 2 and our proposed Module 2 algorithm, which attain the higher accuracy when compared to existing algorithm.

3.6 TESTING PREDICTION TIME

The testing prediction time is defined as the time taken to predict the precise fault.

Table 3: Overall Prediction using Existing and Proposed

S.no	Algorithm	Total (sec)
1	KNN	0.51
2	PNN	0.064
3	RBN	20.6307
4	PSO-SVM	0.05033
5	PROPOSED	0.068

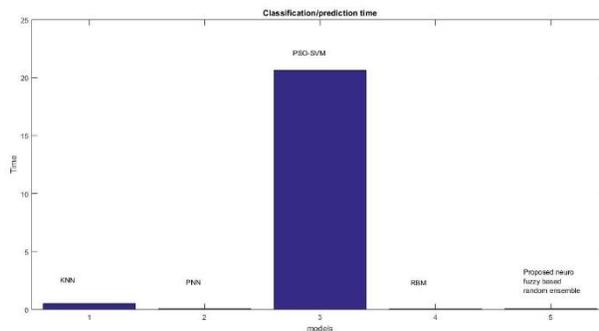


Figure 19. Overall prediction using Existing and Proposed

In the above fig 19 that describe the overall prediction comparison of our proposed algorithm and existing algorithm such as KNN, PNN, RBN, PSO-SVM and proposed values are plotted in the table:3.Finally our proposed Module 2 classifier achieve less prediction time when compared to all other existing algorithm and also precisely diagnose the fault with 0.068 secs which is quite higher. This time is acceptable since we do training twice and we are receiving this less time.

3.7 COMPARISON OF DIAGNOSIS ACCURACY

The Diagnosis Accuracy is defined as the overall probability that a fault will be correctly classified based on the learning sample data set. The Diagnosis Accuracy formula is described below

$$\text{Diagnosis Accuracy} = \frac{a+d}{a+b+d+c} \quad (19)$$

Table 4: Comparison of Diagnosis Accuracy Proposed and Exiting Method

S.No	Features Algorithm	Classifier Algorithm	No. of training samples	No. of testing samples	No. of classes	Diagnosis accuracy
1	LCD-SVD	CRO-SVM	240	80	4	100
2	TDF-FDF	PNN	240	80	4	94.38
3	TDF	Random forest	200	200	4	98.04
4	Module 1	Module 2	225	50	8	98.28

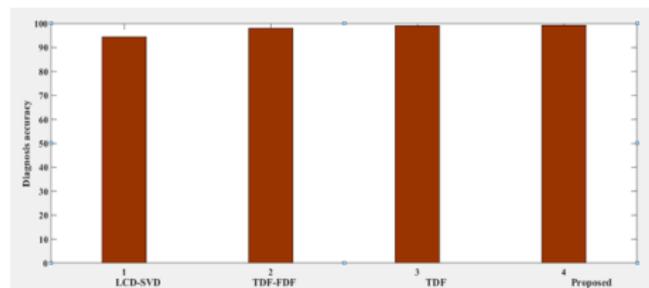


Figure 20. Diagnosis Accuracy of different and Proposed Method

In the above figure 20, that describes the comparison of different existing feature selection method and our proposed for fault diagnosis of rotating machine. In existing work large data set are used to extracting the selected features for diagnosing the fault. Similarity, in this work we are focusing to learn the large number of raw vibration signal for necessary features selection. Table 5 describes the training and testing samples for accurate feature selection using different classes for features extraction. Overall perspective of our proposed feature selection technique attains higher accuracy for selecting the features because the training data set is huge compared to existing works on techniques such as LCD-SVD, TDF-FDF and TDF which is easily attainable to extract the feature. But our proposed feature such RMS, Crest factor and Kurtosis, which are not easily achievable to extract the feature but in this work our proposed algorithm to extract the accurate needed feature easily with the help of stochastic nature. Finally our proposed diagnosing accuracy value is being increased 98.28 when compared to all other existing classifiers like CRO, PNN, etc,

3.8 COMPARISON OF DIAGNOSIS NOISE

Diagnosis Noise is most easily defined from the Mean Square Error(MSE). If we consider a noise-free $m \times n$ mono-component feature I and its noisy approximation K , MSE can be calculated as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - k(i, j)]^2 \quad (20)$$

Peak Signal to noise ratio (PSNR) is measured in dB and is defined as,

$$PSNR = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \quad (21)$$

Where, MAX_I = maximum possible error value of the vibrated signal.

Table 5: Comparative Chart of Results of Diagnosis in Various Noise Environment

Diagnosis Classifier	12dB	13dB	14dB	15dB	16dB	18dB	20dB	22dB	24dB	26dB
Random Forest	74.78	85.82	92.95	95.34	97.74	98.60	99.00	99.26	99.46	99.53
ELM	65.53	69.53	73.01	76.39	79.72	85.48	91.40	96.81	98.83	99.37
PNN	63.25	71.64	79.16	84.84	88.77	93.43	96.51	97.81	98.28	98.87
SVM	66.87	73.32	78.85	83.59	87.66	92.28	95.68	97.24	98.11	98.67
Proposed	72.98	76.28	80.95	84.64	87.56	93.51	97.89	98.28	99.68	99.73

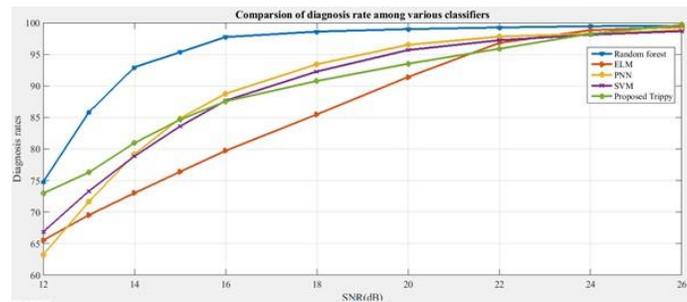


Figure 21. Results of Applied Classifiers with Different Signal to Noise Ratio (SNR)

In the above Figure 21 it is clear that proposed Module 2 Classifier has statistically substantial advantage over the various methods of comparison while processing the test samples at different degrees or levels of noise. The given values in Table 4, for Extreme Learning Machine, Probabilistic Neural Network and Support Vector Machine, a noticeable decline appears when the SNR is lowered below 22dB. However, our proposed Module 2 notably performs well given a longer range of SNR, due to mainly the denoising ability of our proposed module.

3.9 TIME CONSUMPTION OF PREDICTION IN DIFFERENT CLASSIFIERS

Time consumption of prediction is the ratio of total time taken for prediction to the time taken for completion.

$$\text{Time Consumption} = \frac{\text{Time taken to predict the features}}{\text{Total time taken for the completion of the process}} \quad (22)$$

Table 6: Time consumption for prediction in different classifiers

S.no	Algorithm	Prediction Time
1	Random forest	5.08 ms
2	ELM	0.60 ms
3	PNN	8.44 ms
4	SVM	0.50 ms
5	Proposed	0.49ms

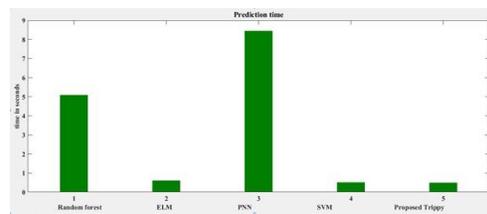


Figure 22. Time Consumption of Prediction in Different Classifiers

In the above Figure 22 that describes the overall diagnosis prediction time compared with existing work and our proposed Module 2 Classifier achieve the less prediction time using a large data set for training and testing. The advantage of our proposed classifier to fulfil in least time prediction in fault diagnosing in the rotating machinery. In table 6 values indicate the prediction time in the comparison of different methods such as random forest achieves the prediction value 5.08ms, ELM method attain 0.60ms, PNN prediction time consumption value is 8.44ms, the prediction of fault diagnosing time SVM method is 0.50ms and our proposed method V-HMNF System achieves less prediction time due to the selective predictive nature of Module 2 classifier, which attain 0.49 ms prediction time when compared to existing our proposed approach has attained better prediction time for fault diagnosis. Consequently, our proposed algorithm automatically detects fault in the rotating vibrated machine in early stage and also saves industry from heavy losses occurring due to machine breakdowns.

In the later course of this work, we deliberate to make changes in this proposed V-HMNFs to improve quality of the final results.

4. CONCLUSION

This work develops an approach for prediction of fault for rotating machinery by utilizing V-HMNFS. Its Module 1 analyses the accurate effective fault features whereas the Module 2 classifier predicts fault occurrence selectively by means of extracted faulty features.

Thus, the proposed system comprising of various techniques, has been effectively implemented on the rotating parts of an air compressor and our system is able to predict faults with comparatively better precision and speed. Fault prediction was done in a run time of 0.021 secs, 98.2% accuracy and prediction time of 0.049ms using our structured feature extraction and classification framework V-HMN system.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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