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Wind Turbine Drivetrain Expert Fault Detection System: Multivariate Empirical Mode Decomposition based Multi-sensor Fusion with Bayesian Learning Classification

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ABSTRACT
To enhance the predictive condition-based maintenance (CBMS), a reliable automatic Drivetrain fault detection technique based on vibration monitoring is proposed. Accelerometer sensors are mounted on a wind turbine drivetrain at different spatial locations to measure the vibration from multiple vibration sources. In this work, multi-channel signals are fused and monocomponent modes of oscillation are reconstructed by the Multivariate Empirical Mode Decomposition (MEMD) Technique. Noise assisted methodology is adapted to palliate the mixing of modes with common frequency scales. The instantaneous amplitude envelope and instantaneous frequency are estimated with the Hilbert transform. Low order and high order statistical moments, signal feature descriptors and randomness measures (entropy) are extracted as truthful features. The feature set is fed into the Bayes classifiers to compare the detection performance. From the analysis it is found that the proposed method is well performed with the Dynamic Bayes Belief Network Classifier showing the detection accuracy of 97.69%. To validate the results, the NRELWind Turbine Drivetrain benchmarking dataset is used.

KEY WORDS: Bayes belief net, fault diagnosis, MEMD, multivariate signal processing, nonstationary signal processing, wind turbine

1 INTRODUCTION

CONDITION-based maintenance is used to predict the upcoming failures by monitoring the system indicators that assess the component deterioration. Maintenance and operating cost influence the economic wind energy generation. Reliable operation & maintenance schemes avoid unscheduled turbine downtime and increase the availability of wind power. The accessibility of the Drivetrain for maintenance is very difficult, because of the tower height, especially in offshore turbines. With the concern of these factors, the maintenance strategies should be intelligent enough to detect the faults at the incipient stages itself. Because of the rapid developments in the sensor technologies, the system dynamics can be measured as temperature, vibrations, acoustic emission, current signature analysis (Abitha Memala & Rajini, 2017) and electro-mechanical impedance (Zhang, Zhang, Chen, & Yang, 2017).

By analyzing these parameters, indicative variation in the system dynamics can be identified

Vibration-based monitoring is found very helpful in rotating machinery. Accelerometer sensors are used to measure the vibration. When the system dynamics are changed, then the vibration signature also changes, hence the vibration is the best candidate to monitor the system variations. Sophisticated signal processing techniques are needed to analyze the vibration signal and to retrieve the fault signatures. By using the fault diagnosis, the vibration signals are mainly classified into the data-driven approach and model-based approaches. In the data-driven approaches, the features are extracted from the raw vibration signal and the fault pattern is recognized from those features.

In the model-based approach, a filtering technique is adapted to model the relationship between the output and input of the system. To develop the model-based fault diagnostic system, the extensive knowledge of the system state variables that affect the input-output relation is needed. The observer based model for nonlinear systems is studied in (Alcorta-

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Garcia, Saucedo-Flores, & Diaz-Romero, 2013). In a data-driven approach, the features are extracted by using digital signal processing algorithms. In this paper, a novel data-driven adaptive fault detection technique is proposed to detect the wind turbine drivetrain faults. Adaptive multivariate decomposition is proposed to obtain mono components from the multicomponent signals. The monocomponent intrinsic oscillation needs to be decomposed so that the useful features can be extracted and fed to the classifiers.

Usually, as an industrial practice, the vibration is measured by using several sensors. The sensor information should be analyzed simultaneously to preserve the advantages of the spatial sparse. The novel decomposition procedure is adapted to estimate the intrinsic mode functions. The vibration signals acquired from wind turbines are non-stationary so the traditional Fourier transform approach is not feasible to extract the truthful features. The time-frequency representation is found to be very useful to analyze the non-stationary signals.

The nonstationary signal processing approaches applied to the rotating machinery is extensively reviewed in (Uma Maheswari & Umamaheswari, 2017) and the combined rotor faults are analyzed using the EMD (Singh & Kumar, 2014). The EMD with ANN is employed for detecting the bearing faults (Ben Ali, Fnaiech, Saidi, Chebel-Morello, & Fnaiech, 2015). From the literature review, it is found that a single channel and single variant EMD suffers from a mode mixing problem. To circumvent the mode-alignment issue in the standard EMD and to facilitate the synchronization among a multi-channel signal analysis, Mandic et al (MANDIC, 2009) proposed a Multivariate EMD (MEMD) that projects the multi-channel envelopes in the n-dimensional domain to fuse the information from multiple sensors. The multivariate EMD is applied to a fault diagnosis of rolling bearings (Lv, Yuan, & Song, 2016). The wind energy conversion systems are much more complex, hence the information available from various sensors to be fused and are to be analyzed synchronously. To preserve the local dynamics, the decomposition should be done in the N-dimensional domain. In this view, the MEMD is an ideal choice for the wind turbine drivetrain fault diagnosis. The fault detection could be automated by using the machine learning algorithms. Features are extracted from the IMFs and are fed to the classifiers to detect the fault signatures.

The Bayesian algorithm's ability in a fault diagnosis is studied extensively in rotating machineries (Agrawal, Panigrahi, & Subbarao, 2017; Cai, Huang, & Xie, 2017; Cai, Liu, & Xie, 2017; Vagnoli, Remenyte-Prescott, & Andrews, 2017; Wang, Wang, Gu, He, & Yan, 2018; Wang, Wang, He, Gu, & Yan, 2017; Zhao, Wen, Xiao, Yang, & Wang, 2017). The Dynamic Bayesian Network is applied to create the multi model of dam condition monitoring (Weihua & Lanyu, 2012).

In some literature, the standard single channel EMD is adopted to analyze the vibration signals in the time-frequency plane. For any mechanical the system, natural frequencies and mode shapes are very important system properties. The vibration source in gear transmission systems are often difficult to access the direct measurement of vibration and are impractical from those sources. Further, the time-varying loads induce vibration in various components. Vibration measured from a single source is highly attenuated while traveling through the gear transmission systems and also distorted by other vibration sources. The vibration measured from the various sensing locations need to be fused so that the common fault frequency scales can be decomposed synchronously. (Jing, Wang, Zhao, & Wang, 2017) proposed the deep learning networks to fuse the features learned from the raw vibration signal. (Chen & Li, 2017) used a two layer sparse encoder for feature fusion. These studies extract features from multiple sensors separately and the fusion is employed. In the proposed study, multivariate signal processing is employed before the feature extraction to improve the feature modeling so as to enhance the fault diagnostics. The standard single channel EMD is limited in a multi-sensor fusion, because of its empirical uniqueness and it depends on the sensitivity to changes in the parameters that make the MEMD a viable option among various Time-Frequency representations.

The noise assisted MEMD is applied to decompose the vibration signal of a hydropower unit. (An & Yang, 2015). The MEMD techniques are applied to study the vibration of structural dynamics (Barbosh, Sadhu, & Vogrig, 2018). A novel Multivariate Empirical Mode Decomposition is adapted for a Multisensor information fusion to analyze the common oscillatory modes from various vibration sources, which those are affected by the fault signatures. Thus, the multi-channel vibration dynamics are preserved, which makes the decomposition a promising tool for further processing. Features from the instantaneous amplitudes and instantaneous frequencies are extracted from the Intrinsic Mode Frequencies, which model the amplitude and frequency demodulation caused by the fault signatures. The Bayes Two Category Learning classifier with the slice topology directed acyclic graph structure is deployed. The classification performance is compared with the Naïve Bayes classifier.

2 MATERIALS AND METHODS

FIGURE 1 describes the flow of the proposed methodology for the truthful fault detection.

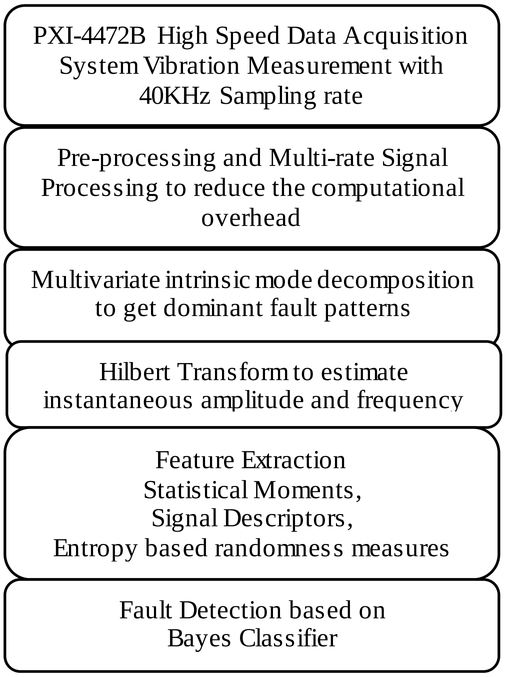

Figure 1: Proposed Method.

2.1 NREL Condition Monitoring Dataset

The vibration data used in this research is obtained from the NREL. Upon request through this URL (Sheng, n.d.) the dataset is available. The above data is acquired from the NREL dynamometer test facility. A detailed description of the dataset can be found in (Sheng, 2013). The test wind turbine is stall controlled to a 750 kW three-bladed upwind turbine, which runs at 1800 RPM rated speed. The NREL Drivetrain has two gearboxes with 1:81.49. The gearbox consists of one low speed planetary gear with two high speed parallel stages. Eight accelerometer sensors (AN3-AN10) are used to collect the vibration signal. The national instruments PXI-4472B is used to collect the vibration data with 40 kHz per channel sampling period. Sensor locations considerably influence the fault diagnostics. In Table 1 the description NREL open access dataset is given. The test data are acquired at the following test conditions: Main Shaft Speed =22.09, RPM, Nominal High-Speed Shaft (HSS), Speed =1800 RPM, and Electric Power (% of rated power) = 50%. The vibration signal is measured from healthy and damaged gearboxes. The dataset is available with 10 minutes damaged state vibration and a 10-minute healthy state vibration.

Table 1: Dataset Description.

Sen	Mounting Location	Component	Fault Type
AN3	Ring Gear Radial 6'o clock	Ring Gear	Scuffing
AN4	Ring Gear Radial 6'o clock	Sun Gear	Fretting Corrosion
AN5	LS-SH Radial	Gear ratio:	-
AN6	IMS-SH Radial	Intermediate Gears	Scuffing
AN7	HS-SH Radial	High Speed	Scuffing
AN8	HS-SH Upwind Bearing	Tapered Roller bearings	Over heating
AN9	HS-SH Downwind Bearing	Tapered Roller bearings	Over heating
AN 10	Carrier Downwind Radial	full-complement cylindrical roller bearings	Fretting Corrosion

2.2 Pre-processing and Angular Domain Resampling

In the rotating machinery, the sources of vibration produce the vibration modes at factors (orders) of rotational speed. To remove the smearing artifacts, angular resampling is widely used. The time increment samples are converted into phase increment samples. Samples are taken for each revolution rather than the time instant increments. The RMS value of the orders are computed with respect to the RPM. The test turbine rated nominal HSS speed is 1800 rpm and 40000 samples per second have been taken. The synchronization time period is retrieved from the turbine RPM profile. The resampling period depends on the order resolution (Brandt, 2011), which represents in terms of the maximum order, RPM profile, and sampling period. The eight sensor data are fused into the single matrix ψ_{mv}. Columns of the ψ_{mv} represent the sensor data and the rows represent the observations. In order to improve the classification accuracy with computational constraints, the single multivariate matrix is segmented into several blocks. 40000 phase incremented samples from each signal channel are used to form a multivariate sub matrix and these sub matrixes are fed into a multivariate empirical mode decomposition.

2.3 Multivariate Empirical Mode Decomposition (MEMD)

To model the multi-channel signal simultaneously in a joint time-frequency plane, an adaptive data-driven approach is introduced in (MANDIC, 2009) whose ability for the accurate analysis is proven in the biomedical signal processing. The wind turbine gear transmission vibrations are typically complex, nonlinear, and are non-stationary multichannel dynamics hence, the multiple oscillatory modes from different channels should be analyzed concurrently to match the IMF in scaling with equal numbers. The algorithm is explained below.

MEMD Algorithm

1. The angular coordinates in an n-dimensional sphere serve the directional vectors of the multi-channel data. The direction vectors are generated by Halton and Hamersley quasi Monte correlation sequences.
2. The input multivariate data is projected along the directional vectors. The projections (pi) are calculated along the uniform angular positions. $\omega^k = \left\langle \omega_1^k, \omega_2^k, \omega_3^k, ...\omega_{n-1}^k \right\rangle$ n-1 sphere for n - variant data.
3. The Extreme Value time instants are estimated for the K number of projections and k time instants are estimated.
4. The spline interpolation is adapted to find the multivariate envelopes. The envelope mean is computed as (m(t)) and m(t) represents the monocomponent intrinsic mode function (IMF)
5. The residual error is computed from the original signal as r(t)=x(t)-m(t).
6. The residual is compared with the threshold value, if the discrepancy between the two adjacent sifting is less than the threshold value then the sifting is terminated.

2.4 Feature Extraction

Instantaneous amplitude and instantaneous frequency are estimated from the IMFs. Features describing the shape of the distributions (statistical moments), complexity measures (entropy), and load/speed independent parameters (signal descriptors) are extracted. Fourteen descriptive parameters such as first to fourth order moments, crest factor, Peak to Peak, time series complexity measures (Sample entropy, Permutation entropy, and Fractal dimension), and spectral flatness measure (Wiener entropy) are extracted from the instantaneous values.

First and Second order moments describe the shape distributions of the time series. The third order moment is used to define the symmetry of the distribution shape. Fourth order moments define the relative peakedness. Faults tend to increase the chaos in the vibration. In particular, the complexity measure describes the chaotic state that holds the information about the randomness of the time series at multiple scales. Figure 2 visualizes the density distribution of the extracted features. The peaks at the density plots illustrates the highest concentration points.

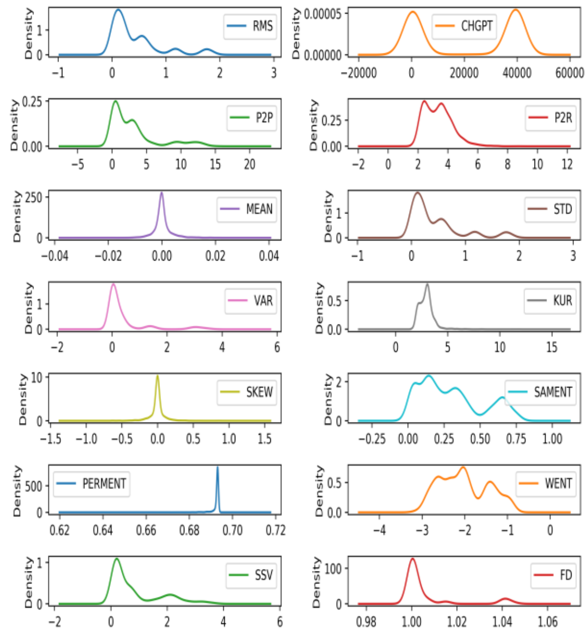

Figure 2. Density Distribution of Extracted Features.

2.5 Automatic Fault Detection

Supervised machine learning is employed for fault detection. The original data set is unlabeled. The Data Set is labeled from faulty and baseline conditions.

2.6 Bayes Belief Network Classifier

Bayesian Belief Networks (BBN) consists of nodes in a directed acyclic graph used to determine probabilistic dependencies between the variables in the featured set (Cooper & Herskovits, 1992; Pearl, 1986). The features represented as variables are in nodes. The conditional probabilities quantify the dependencies among the variables. The weights are adjusted in such a way to strengthen the dependency. Loops are not allowed in the network structure. The Bayesian network deduces the probability distribution functions of the attributes dependent on a particular class C from the training set; $P_\phi(F1, F2, F3.....FN, C)$. The dependency of children with parents is computed as (4).

$$p(f^{K} \mid \chi) = \prod_{i}^{|K|} p(f_{K_i} \mid \chi) \quad (1)$$

where f is the evidence of dependency of K children and χ is the particular node f_{Ki} is the values of the probability of the child state. BBN learning assumes a subset of attributes from the given training set and is conditionally independent. BBN classifies the attributes by maximizing the posterior probability.

2.6.1 Naïve Bayes Classifier

Naïve Bayes is a probabilistic classifier that computes the weights based on the assumption of occurrence of an attribute and is independent of the occurrences of other attributes in the training set. Naïve Bayes learning considers each attributes that contributes towards the learning. The contribution of the particular attribute to the class is determined from the conditional probability estimated as the relative frequency samples in the Gaussian density function. The Classification target is considered as the parent node and the attributes form the child nodes. The graph is directed from the parent to child and other connections are not permitted. The Naïve Bayes rule (5) is employed when the dependency relationship among the attributes has uncertainties.

$$p(\lambda_i \mid \mathrm{X}) \propto \prod_{j=1}^{n} p(y_j \mid \lambda_i) \qquad (2)$$

3 RESULTS AND DISCUSSION

3.1 Angular Domain Resampling

TO weigh the ability of the proposed method in the wind turbine drivetrain fault detection, the experimental analysis is carried out on the NREL GRC dataset. Synchronous (angular) resampling is done with the Speed (rpm) profile. The instantaneous RPM profile is used to determine the resampling interval. The accuracy of this method depends on the degree of uncertainty introduced by the instantaneous RPM. The Savitzky-Golay smoothing filter is the weighted moving average filter that fits the specific order in the polynomial function in a least square sense and the smoothing filter output has slow variations, so that the trends in the data can be easily identified.

3.2 Multivariate Decomposition of the common Intrinsic Modes

The MEMD decomposes the multi-component vibration signal into its amplitude and frequency modulated (AM-FM) mono-components. The MEMD has the mode alignment property that aligns the common scales present in each variant into common oscillating modes within the multivariate IMFS. In this research work, the Multivariate data are segmented into 239 blocks and each segment has 40000 phase incremented samples. The MEMD decomposes each block into $8*14*40000$ IMFs sets.

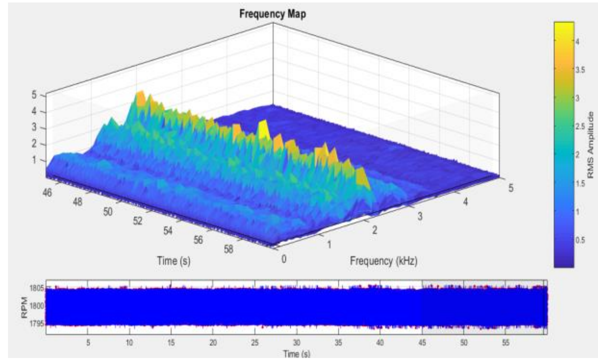

Figure 3. **RPM Frequency Map.**

The high amplitude peaks are visible at 2KHz.The smearing atrifacts visible in the frequency map (Figure 3) are removed by angular resampling in Figure 4. Vibration peaks are dominant in 67-71 orders. It is manifested that the number of IMFs extracted from all sensors are the same with a common frequency scale and each IMF represents the unique oscillatory mode presence in the octet variant data. The first ten IMFs contain high frequency modulations; those are considered for the feature extraction. The IMFs 11-14 have low frequency components with smaller amplitude variations hence those are omitted from further analysis.

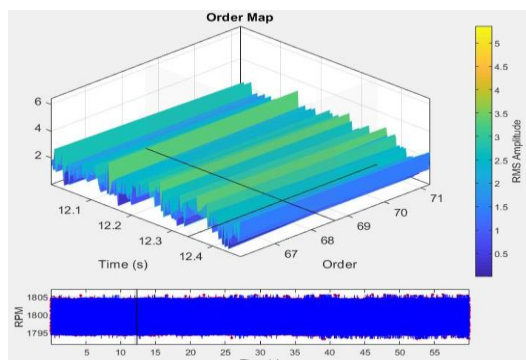

Figure 4. **RPM Order Map.**

Fault signatures are detected from other IMF modes. Irrespective of the frequency contents and equal numbers of the IMFs are extracted from the octet variant signal shown in Figure 5.

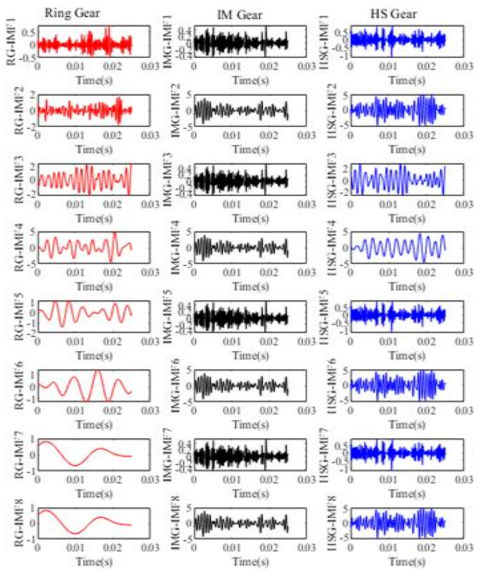

Figure 5. Common Intrinsic Mode Decomposition by Multivariate Signal Processing. Columns Represent Sensors, Rows Represents IMFs.

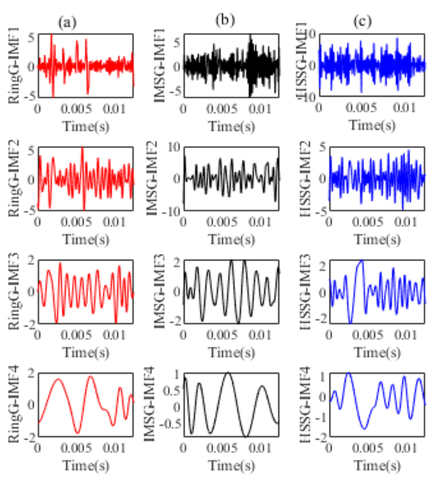

Figure 6. Empirical Mode Decomposition (a) Ring Gear Vibration (b) IMS Gear Vibration (c) HSS Gear Vibration.

The decomposition result is compared with a single channel EMD in Figure 6 and the mode mixing is clearly evident in Figure 6. Since the samples are represented in an angular domain (sample per revolution) the oscillating modes across the IMF is uniquely decomposed. Without angular resampling, the classification accuracy for the same feature set is found to be around 50% only. Further, the performance of the MEMD is improved with a smoothing filter that filters out the unwanted white noise.

3.3 Feature Extraction and Feature Selection

Instantaneous Amplitude and Instantaneous Frequency are extracted by using the Hilbert Transform and statistical descriptors and complexity measures are extracted. The feature set is labelled with faulty and healthy classes.

Figure 7 shows the heatmap of the extracted features. Table 2 demonstrates the average values of the extracted features.

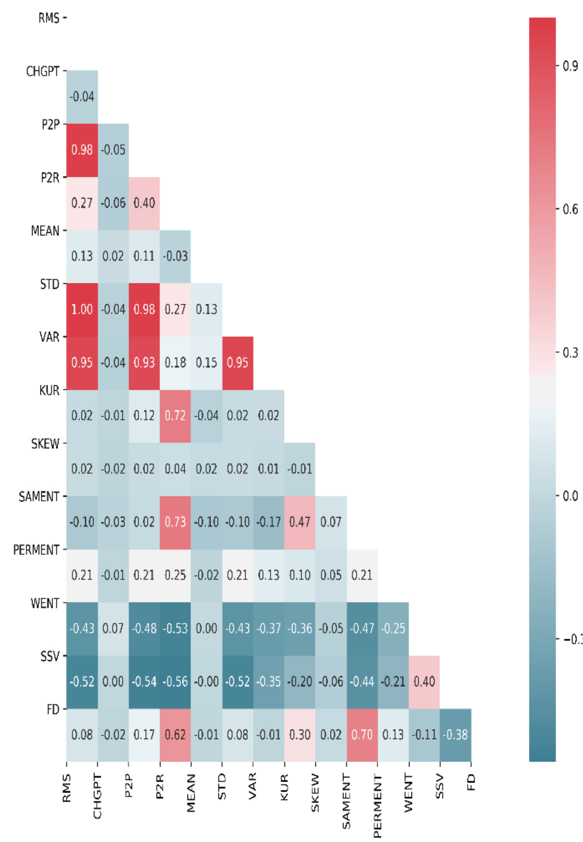

Figure 7. Feature Correlation Heat Map.

3.4 Bayes Classification

The dataset contains 3500 fault class observations and 3250 healthy class observations. A 5-fold cross validation training is employed. The entire data set is sliced into 5-folds. Four-folds are used for training and 1-fold is used for testing. The training is iterated to k times. The entire dataset is used for training as well as the testing improves the detection performance. In this work, k=10 is adapted. The directed acyclic graph network model is based on conditional probability distribution and model dependencies of the features with respect to the target. The features are modelled as stochastic variables and the model is built based on a maximum posterior probability distribution.

Table 2: Average Values of Extracted Features.

Features	Faulty Class	Healthy Class
RMS	0.54	0.21
Change Points	2.05×10^{4}	2.05×10^{4}
Peak to Peak	3.73	1.54
Crest Factor	3.30	3.37
Mean	3.3×10^{-4}	-2.44×10^{-4}
Standard Deviation	0.54	0.21
Variance	0.57	0.09
Kurtosis	2.93	2.83
Skewness	-0.01	0.01
Sample Entropy	0.25	0.36
Permutation Entropy	0.69	0.64
Wiener Entropy	-2.05	-1.95
Spectral Flatness	0.84	0.87
Fractal Dimensions	1.00	1.65

3.4.1 Naïve Bayes Classifiers

The Target class serves the parent node and the attributes used in the feature set forms the children's leaves. It is observed that the attributes are conditionally independent with the given target class. The confusion matrix for the naïve Bayes classifier is shown in Table 3. The overall classification accuracy results into 59.40%. The reciever operating characteristics (ROC) of the Naïve Bayes classifier is shown in Figure 8. Some attributes have influence over other attributes, hence for this feature set the Naïve Bayes classification accuracy is low. The area under the ROC is 0.829.

Table 3. Confusion Matrix of Naive Bayes.

	Faulty	Healthy
Faulty	1222	1658
Healthy	197	1493

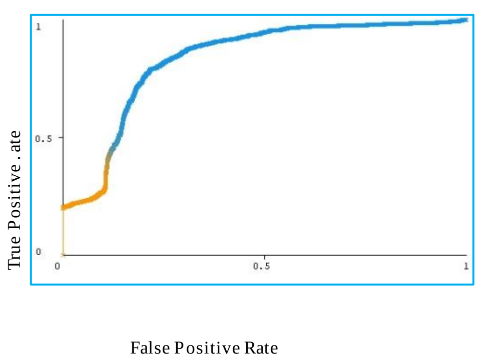

Figure 8. Receiver Operating Characteristics for the (ROC) area is 0.829.

3.4.2 Bayes Belief Net Classifiers

The Bayes Belief Net is the complex directed acyclic graph (DAG) structured with the attributes. The Bayes Net computes the conditional probability of the sub set of attributes to the target class. The connected nodes posterior probability is computed while all other nodes are considered as conditionally independent. The Dynamic Belief networks (DBN) have the slice topology. The observation parameters are tangled together across the slices. Conditionally the probability for the sub sets of the nodes is computed as in the topological order specified in the fault DBN. The network structure is learned by conditional independent tests that unwarp the casual structure. The conditional probability of the independence is computed as the posterior distribution among two variables to locate the edges. Table 4 shows the confusion matrix of the Bayes Net Classifier. The overall accuracy is 92.57%.

Table 4. Confusion Matrix of the Bayes Belief Net.

	Faulty	Healthy
Faulty	2581	299
Healthy	97	1594

The Two Category Bayes Net classifier performances are an evaluated area under the ROC as shown in Figure 9.

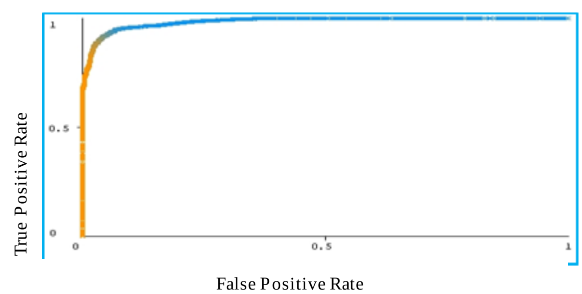

Figure 9: Receiver Operating Characteristics for the (ROC) Area is 0.989.

The posterior joint probability distribution of each subset attributes is computed to train the Bayes Net. The model is fitted into the Maximum likelihood parameter estimation between the sub sets. At learning, the cardinality is set to 0 to 3 to calculate the probability. Table 5 compares the Naïve Bayes and belief net classifiers performance. Comparison of the classifier error characteristics is shown in Figure 10.

Table 5. The Classifier Performance Measure: Weighted Average.

Performance Measure	Naive Bayes	Bayes Belief Network
True Positive Rate	0.594	0.913
False Positive Rate	0.286	0.075
Precision	0.718	0.919
Recall	0.594	0.913
F-Measure	0.586	0.914
MCC	0.321	0.822
ROC Area	0.829	0.975
PRC Area	0.824	0.979

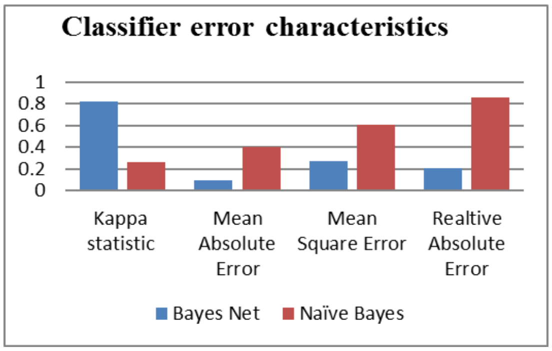

Figure 10. Error Characteristics of Classifier.

The MEMD method with the Bayesian classification is compared with the existing Hilbert Hung Transform, and Wavelet Transform. The classification performance metrics is tabulated in Table 6.

Table 6. Comparison with the Existing Methods.

Metrics	HHT	CWT	MEMD
Accuracy	57%	73%	92%
Sensitivity	52%	73%	91%
Specificity	49%	69%	84%
Precision	48%	74%	91.9%

4 CONCLUSION

A novel frame work for the expert wind turbine drivetrain fault detection system based on the Multivariate Empirical Mode Decomposition (MEMD) with the Dynamic Bayesian Belief network (BBN) classifier is proposed. The turbine drivetrain faults have multiple vibration sources hence the data is acquired with multiple sensors. The sensors are fused at the sensing information level with the help of the MEMD. The MEMD is an effective methodology to decompose the multiple vibration time series simultaneously. The proposed method effectively applies the mode alignment property of the MEMD for truthful intrinsic mode function extraction from multiple sources synchronously. Reliable features are crafted from the instantaneous parameters that input to the Bayes classifier models. The Naïve Bayes and Bayes Net classifier models are fitted into a feature space. The analysis shows that the Bayes Net learns the features effectively and the fault detection rate is 92.57% with the Bayes Net, whereas in the Naïve Bayes, the classification accuracy is 59.4%. The proposed method is validated with the NREL Wind Turbine Drivetrain Dataset.

5 ACKNOWLEDGMENT

WE extend our gratitude to NERL for providing the wind turbine gearbox vibration condition monitoring benchmarking datasets.

6 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

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8 NOTES ON CONRIBUTORS

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